TAKEOVER LIKELIHOOD MODELLING:
TARGET PROFILE AND PORTFOLIO RETURNS

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ABSTRACT

This thesis investigates four interrelated research issues in the context of takeover likelihood modelling. These include: (1) the determinants of target firms' takeover likelihood, (2) the extent to which targets can be predicted using publicly available information, (3) whether target prediction can form the basis of a profitable investment strategy, and – if not – (4) why investing in predicted targets is a suboptimal investment strategy. The research employs a UK sample of 32,363 firm-year observations (consisting of 1,635 target and 31,737 non-target firm-year observations) between 1988 and 2010.

Prior literature relies on eight (old) hypotheses for modelling takeover likelihood – determinants of takeover likelihood. Consistent with prior studies, I find that takeover likelihood increases with the availability of free cash flow (Powell (1997, 2001, 2004)), the level of tangible assets (Ambrose and Megginson (1992)) and management inefficiency (Palepu (1986)), but decreases with firm age (Brar et al. (2009)). The empirical evidence lends no support to the firm undervaluation, industry disturbance, growth-resource mismatch or firm size hypotheses (Palepu (1986)). I extend prior research by developing eleven (new) hypotheses for target prediction. Consistent with the new hypotheses, I find evidence that takeover likelihood is an inverse U-shaped function of firm size, leverage and payroll burden. Takeover likelihood also increases with share repurchase activity, market liquidity and stock market performance and decreases with industry concentration. As anticipated, the new hypotheses improve the within-sample classification and out-of-sample predictive abilities of prior takeover prediction models.

This study also contributes to the literature by exploring the effects of different methodological choices on the performance of takeover prediction models. The analyses reveal that the performance of prediction models is moderated by different modelling choices. For example, I find evidence that the use of longer estimation windows (e.g., a recursive model), as well as, portfolio selection techniques which yield larger holdout samples (deciles and quintiles) generally result in more optimal model performance. Importantly, I show that some of the methodological choices of prior researchers (e.g., a one-year holdout period and a matched-sampling methodology) either directly biases research findings or results in suboptimal model performance. Additionally, there is no evidence that model parameters go stale, at least not over a ten-year out-of-sample test

period. Hence, the parameters developed in this study can be employed by researchers and practitioners to ascribe takeover probabilities to UK firms.

Despite the new model's success in predicting targets, I find that, consistent with the market efficiency hypothesis, predicted target portfolios do not consistently earn significant positive abnormal returns in the long run. That is, despite the high target concentrations achieved, the portfolios generate long run abnormal returns which are not statistically different from zero. I extend prior literature by showing that these portfolios are likely to achieve lower than expected returns for five reasons. First, a substantial proportion of each predicted target portfolio constitutes type II errors (i.e., non-targets) which, on average, do not earn significant positive abnormal returns. Second, the portfolios tend to hold a high number of firms that go bankrupt leading to a substantial decline in portfolio returns. Third, the presence of poorly-performing small firms within the portfolios further dilutes its returns. Fourth, targets perform poorly prior to takeover bids and this period of poor performance coincides with the portfolio holding period. Fifth, targets that can be successfully predicted tend to earn lower-than-expected holding period returns, perhaps, due to market-wide anticipation.

Overall, this study contributes to the literature by developing new hypotheses for takeover prediction, by advancing a more robust methodological framework for developing and testing prediction models and by empirically explaining why takeover prediction as an investment strategy is, perhaps, a suboptimal strategy.

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If I have seen further, it is by standing on the shoulders of giants.

Isaac Newton

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AUTHORS DECLARATION

'I declare that, except where explicit reference is made to the contribution of others, this dissertation is the result of my own work and has not been submitted for any other degree at the University of Glasgow or any other institution'.

Signature:

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CHAPTER 1 INTRODUCTION

1.1 Introduction

Typically, organisations undergo some form of restructuring during their life time. Merger and acquisition activity (M&A, henceforth) substantially impacts on participating firms and their stakeholders (including investors, competitors, management, employees, communities and regulators) over several years. It is generally thought that M&A is pursued by firms in search of synergies or by entrenched managers seeking to serve their own interests. Nonetheless, 'synergy' and 'managerial self-interest' are illusive or, at best, multidimensional constructs. Beneath these constructs, little can be said about what drives the phenomenon or whether some firms are more likely to be involved in M&A activity than others.

Indeed, there are several reasons why understanding this phenomenon is important for different stakeholders. Some of these reasons are highlighted here but discussed in more detail in section 2.3. Policy makers are responsible for enacting a regulatory framework to guide M&A activity and for assessing the desirability of proposed mergers. Understanding why this activity occurs and the motivations of the parties involved is critical to making an informed decision. 'Is my firm a takeover target?' is possibly a key question that resonates with many managers, given the recurrent finding that executives of acquired firms are typically ousted. While target executives might shun takeovers, target investors typically benefit – earn substantial abnormal returns – from M&A activity (see, for example, Franks and Harris (1989) and Georgen and Renneboog (2003)). This established finding motivates the next question. 'Is identifying and investing in potential targets the recipe of a winning investment strategy for the investment community?'

These are clearly important questions for both researchers and practitioners. Indeed, a number of attempts have been made to address these questions. Nonetheless, the literature is riddled with several gaps and a general lack of consensus – something this research aims to address. This thesis investigates four interrelated research issues: (1) the determinants of target firms' takeover likelihood, (2) the extent to which targets can be predicted using publicly available information, (3) whether target prediction can form the basis of a profitable investment strategy, and – if not – (4) why investing in predicted targets is, perhaps, a suboptimal investment strategy.

The first question aims to shed light on the different motives of takeovers by focusing on the profile of takeover targets. The objective is to understand what factors differentiate potential targets from non-targets. As will be discussed further in section 1.2, the fact that little is known about the characteristics of takeover target has been highlighted by prior studies (e.g., Ambrose and Megginson (1992) and Powell (1997)). As will be discussed in section 1.4.2, this thesis extends prior literature by proposing and testing new hypotheses on the characteristics of targets. The second question is empirical in nature. It assesses whether improved knowledge of the characteristics of targets (obtained from the first research question) can support the development of a model which can predict future targets. As will be discussed in section 1.4.3, this thesis directly contributes to the area by introducing methodological improvements for developing and testing target prediction models.

The third research question focuses on takeover prediction from an investor's perspective. The objective is to evaluate whether investors can earn abnormal returns by investing in predicted targets. The efficient market hypothesis (further discussed in section 2.4) suggests that investing in a portfolio of predicted targets is unlikely to yield abnormal returns for investors as share prices reflect takeover probability. Therefore, the third research question also serves as a test of the efficient market hypothesis. Assuming that the market is efficient (as per the third research question), the fourth research question focuses on understanding how the efficient market hypothesis unfolds in this setting. That is, it seeks to explain why portfolios of predicted targets earn normal returns even though targets within such portfolios earn substantial abnormal returns.

Section 1.2 contextualises the study by briefly summarising the body of research on takeover prediction modelling in order to highlight the main gaps in the literature and illustrate how the current research fits within and contributes to the research area. A majority of related research has been conducted using samples of US firms. The thesis employs a UK sample of 32,363 firm-year observations (consisting of 1,638 target firm-year observations and 30,725 non-target firm-year observations) between 1988 and 2010. The development of the sample is fully discussed in section 4.2. The goal of section 1.3 is to discuss why the UK institutional context is an equally valid (or even a better) setting for takeover prediction modelling when compared with the US. Section 1.3 also reviews the UK takeover market and its underlying regulatory context.

1.2 Background of current research

Several studies use the takeover market as a context to explore different hypotheses and theories in finance. Prior studies have explored the drivers of the takeover decision such as role of firm asset structure (Ambrose and Megginson (1992)), cash management policy (Powell (1997)) and management performance (Hasbrouck (1985)), amongst others. These studies improve our understanding of the characteristics of takeover targets and the factors that make certain firms attractive to bidders. Attempts to empirically quantify the vulnerability of different firms to takeovers can be seen as a natural extension to this literature. Studies such as Vance (1969) and Palepu (1986) pool together the cross section of characteristics of takeover targets to develop takeover vulnerability assessment models. These risk assessment models have increasingly become popular – perhaps, a spill-over effect of the success of bankruptcy prediction models such as Altman's Zeta (Altman (1968)).

The major theoretical developments in the area of takeover prediction modelling have been in terms of advancing (and testing) theory-based hypotheses on the factors that differentiate takeover targets from non-targets. These hypotheses are generally referred to as 'prediction hypotheses'. Palepu (1986) advanced five key prediction hypotheses (including: the inefficient management hypothesis, growth-resource mismatch hypothesis, firm undervaluation hypothesis, industry disturbance hypothesis and the firm size hypothesis) which have been adopted across the literature. Ambrose and Megginson (1992), Powell (1997) and Brar et al. (2009) augment this list of hypotheses by advancing the tangible assets hypotheses, the free cash flow hypotheses and firm age hypotheses, respectively. These hypotheses are fully discussed in chapter 3. The set of eight hypotheses forms the framework used by a majority of prior studies for the development of takeover prediction models.

Despite its growing popularity, the target prediction literature is fraught with inconsistencies and several apparent gaps. These inconsistencies and gaps in the literature are discussed in chapter 2. Nonetheless, three of these gaps which initially motivated this study, are worth mentioning at this stage. First, the characteristics of targets are not fully known or understood. As will be discussed in chapter 2, the characteristics appear to vary both across samples (countries, settings and industries) and over time. This dynamism coupled with the fragmented nature of the literature has made the development of a reliable takeover target profile an onerous task. Second, the prediction framework used in prior studies, perhaps, tends to over-simplify the strategic motives surrounding the takeover decision. Prior studies have used different combinations of the eight prediction hypotheses (noted above) to develop target prediction models which aim to capture the thought process and motivations of managers engaged in acquisitions. It is clearly unlikely that these eight hypotheses comprehensively reflect the complexities in the M&A decision[1]. Third, the methodologies used by prior researchers to develop and test prediction models are not robust and can be substantially improved. Some of these methodological weaknesses are discussed in section 2.6 and explored in chapters 5, 6 and 7. The lack of robustness and consistency in prior research frustrates efforts to explore any of the pertinent research issues (discussed in section 1.1) using results from prior research.

This study seeks to develop a model that uses publicly available information to predict firms that will attract takeover bids in the future. Its underlying assumption is that targets are not arbitrarily selected by bidders i.e., bidders choose their targets strategically to meet certain objectives. If the choice of targets is arbitrary then, it is unlikely that targets can be predicted. It can also be reasonably assumed that bidders' strategic objectives might change from one point in time to another, shaped by industry dynamics and external macroeconomic conditions. If this is the case, a key part of this modelling exercise is to understand the objectives of bidding firms so as to identify those general conditions (firm characteristics, industry dynamics and macroeconomic environments) that make some firms suitable targets to an average bidder in certain periods. The natural starting point for such analyses is the theory on why takeovers occur, why firms are acquired and what factors potential moderate the decision to engage in takeover activity (explored in chapter 3). If these characteristics, their dynamics and interrelationships can be identified, the profile of a typical target can be developed. Predicting potential targets therefore will be consistent with identifying firms which share the profile of a typical target.

[1] This contention is supported by evidence from the general corporate restructuring literature. For example, Powell and Yawson (2007) show that these hypotheses are also useful in modelling other restructuring events including bankruptcies, divestitures, and layoffs. The implication of this finding is that this framework is generalist and hence unlikely to be an optimal framework for takeover likelihood modelling.

As cited above and discussed further in section 2.3, takeover likelihood modelling is of relevance to different stakeholders. Given the consensus that takeover targets gain enormously from takeover activity, prior studies focus on the relevance of takeover likelihood modelling to investors. Studies (such as Palepu (1986), Walter (1994), Powell (2001, 2004) and Brar et al. (2009)) investigate the extent to which prediction models can identify suitable investment opportunities for investors. A majority of prior studies have been conducted using US firms. A UK sample is selected for the current study. The next section explains the underlying rationale for this choice and discusses some of the relevant and unique characteristics of the UK institutional context which makes it an optimal setting for investigating firm-specific factors that drive the takeover decision.

1.3 The UK institutional context

1.3.1 Overview

The differences between the shareholder (Anglo-American) and stakeholder (Continental Europe and Japan) corporate governance systems have been used to explain the cross-sectional differences between countries, in terms of firm financing (capital structure), firm ownership (banks versus shareholder model), and the role of the market for corporate control, amongst others (Aguilera et al. (2006)). Prior research, generally, assumes homogeneity under each of these categories. In the case of the shareholder institutional systems (which predominates in the UK and US), this homogeneity argument is not unfounded as the UK and the US, for example, share more similarities than differences from a corporate governance perspective (Miller (2000) and Renneboog et al. (2007)). The tendency has been for empirical results and conclusions obtained in the US to be extrapolated and used for making inferences in the UK.

In terms of takeover prediction and target characteristics modelling, a majority of studies (see, for example, Palepu (1986), Bartley and Boardman (1986, 1990), Ambrose and Megginson (1992), Walter (1994), Espahbodi and Espahbodi (2003), Cremers et al. (2009) and De and Jindra (2012), amongst others) have focused on a US context for obvious reasons – primarily, a large sample size, data availability, a well-developed capital market, an active takeover market and the potential for research impact. Only a handful of studies have investigated these issues in the UK context. In fact, with the exception of studies by Barnes (1990, 1998, 1999, 2000), Powell (1997, 2001, 2004)) and Powell and Yawson (2007) which employ the UK context, most studies in the area focus on the US context.

This study focuses on the UK for two main reasons. First, the UK (like the US) has an active takeover market (further discussed in section 1.3.4). Evidence provided by Sudasanam (2003) confirms that the US and UK have historically been the largest and most active takeover markets. This large sample allows for empirical validity of analysis and relevance (or generalisability) of research results. Second, the UK, perhaps, presents a unique institutional context for understanding the factors (firm observable characteristics) that drive takeovers. Despite the many similarities between the UK and US, the two contexts differ substantially in terms of takeover regulatory regimes (see Miller (2000), Toms and Wright (2005), Williams and Conley (2005), and Armour et al. (2007)). In section 1.2.2, I discuss the divergence of US and UK takeover regulations. In section 1.2.3, I explain why, of the two countries, the UK provides a cleaner context for modelling takeover likelihood and understanding the characteristics of takeover targets. In section 1.2.4, I discuss the historical M&A trends in the UK.

1.3.2 The divergence of US and UK regulations

The differences between the US and UK takeover regulation, as well as, the origins of these differences, have been discussed in contemporary legal literature (see, for example, Johnston (2007) and Armour et al. (2007, 2011)). The implications of such differences on the modelling of takeovers and the generalisation of empirical conclusions have been ignored in the accounting and finance literature. The legal literature generally suggests that the two contexts (UK and US) are startlingly different in their regulation of unsolicited tender offers, both in mode and substance.

As discussed in Armour et al. (2011), the 1968 Williams Act is the key US takeover regulation. It imposes important disclosure and procedural requirements for tender offers for US firms but (deliberately) fails to regulate the conduct of target boards in responding to and resisting takeover bids (Armour et al. (2011), p. 241). Different US states have tended to regulate takeovers differently, with two key dichotomies arising. While some states (such as California and Texas) have no formal antitakeover laws, other states (such as Pennsylvania, Ohio, Massachusetts, Wisconsin and Delaware) are noted for their protectionist-type policies (Karpoff and Malatesta (1990), Armour et al. (2007, 2011)). Karpoff and Malatesta (1990) find that over 35 US states use a combination of control-share acquisition, fair-price and freeze-out laws, which deter bidders from attempting hostile acquisitions. In addition, some states explicitly allow target management to mount appropriate takeover defences. In reference to the Delaware[2] law, Armour et al. (2011) note that 'where a target board has reason to regard a hostile bid as a threat to legitimate corporate policy and shareholder interests, the board has both the power and the duty to interpose itself between the offeror and the shareholders and, where necessary, take defensive measures that are not disproportionate to the threat' (p. 243). This regulatory approach (which appears to be shared by other states) gives the board the power to set up pre-bid and post-bid defensive strategies to fend-off unsolicited tender offers. Here, the regulation gives management and not the shareholders, the responsibility of deciding whether a takeover should proceed.

The approach to M&A regulation in the UK is much different. M&A in the UK is regulated by the City Code, issued by the Takeover Panel. A key distinguishing feature of the City Code is that it 'mandates strict neutrality of target boards, prohibits directors from installing defensive measures without shareholder approval, and imposes a mandatory rule requiring bidders that acquire over thirty percent of the target company's voting rights to extend the offer to all shares of all classes subject to the offer' (Armour et al. (2011), p. 243). Some of these distinguishing features are specified in General Principle 3[3] and Rule 21[4] of the City Code.

There is thus a clear regulatory divergence between the UK and US, with the US (or UK) system placing the ultimate responsibility for deciding on the merits of a takeover on management (or shareholders). This has implications on the role of the market for corporate control in monitoring management performance. Possibly, the US system of regulation entrenches inefficient management teams by protecting management from outside corrective forces or an active takeover market (Karpoff and Malatesta (1990)).

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2 The antitakeover regulation in the state of Delaware is particularly important as a large proportion of US firms are incorporated in Delaware (Amour et al. (2011)).

3 General Principle 3 states that, 'The board of an offeree company must act in the interests of the company as a whole and must not deny the holders of securities the opportunity to decide on the merits of the bid.'

4 Rule 21 states that, 'During the course of an offer, or even before the date of the offer if the board of the offeree company has reason to believe that a bona fide offer might be imminent, the board must not, without the approval of the shareholders in general meeting: (a) take any action which may result in any offer or bona fide possible offer being frustrated or in shareholders being denied the opportunity to decide on its merits; or (b) (i) issue any shares or transfer or sell, or agree to transfer or sell, any shares out of treasury; (ii) issue or grant options in respect of any unissued shares; (iii) create or issue, or permit the creation or issue of, any securities carrying rights of conversion into or subscription for shares; (iv) sell, dispose of or acquire, or agree to sell, dispose of or acquire, assets of a material amount; or (v) enter into contracts otherwise than in the ordinary course of business.'

These differences are also likely to have substantial implications on takeover prediction modelling. In section 1.3.3, I discuss how these regulatory differences, potentially, makes the UK an optimal sample for studying the effect of observable firm characteristics on firm takeover likelihood.

1.3.3 The effect of antitakeover provisions on prediction modelling

Takeover target modelling involves identifying firm (observable) characteristics and the enabling environments (such as the level of economic growth) which spur bidders to make bids for these firms at certain periods. In this section, I argue that the UK (as compared to the US) provides a cleaner context for takeover likelihood modelling. As will be discussed in section 2.5, firm financial characteristics and market/macroeconomic variables, which are both readily observable, can be used to capture time-varying firm and environmental characteristics. Under the general assumption that takeovers are non-random events[5], the likelihood of a firm (*i*) becoming a target (or receiving a takeover bid) in a period (*T*) can be modelled as a function of its characteristics (α_i) in the most recent period (*T*–1) in which these are observable.

$$Prob_{iT} = f(\alpha_{iT-1}) \dots \dots \dots Eqn\ 1.3.3(1)$$

Even though the agency theory (Jensen and Meckling (1976)) posits that target managers are inclined to shun takeovers and protect their interest, empirical research on target prediction has ignored the implication of this tendency on takeover likelihood modelling. When the ability of management to shun takeovers is restricted (e.g., by regulation such as in the UK as discussed in section 1.3.2), this empirical assumption is, perhaps, valid. When this is not the case (e.g., when state laws allow for the protection of incumbents such as in the US as discussed in section 1.3.2), there is unlikely to be a clear relationship between firm characteristics and takeover likelihood. Here, takeover likelihood will be partly influenced by firm observable characteristics (α), the applicable antitakeover laws[6] (ϑ), the target's existing (pre-bid) takeover defences (γ) and the target's likely response to a takeover approach (δ).

$$Prob_{iT} = f(\alpha_{iT-1}, \vartheta_{T-1}, \gamma_{iT-1}, \delta_{iT-1}) \dots \dots \dots Eqn\ 1.3.3(2)$$

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[5] That is, the identification of targets is a systematic process and bidders select targets that will allow them to achieve a certain objective.

[6] These laws could include control share acquisition laws, fair price laws and freeze-out laws (Karpoff and Malatesta (1990))

This relationship is enforced by the fact that bidders incur substantial search and negotiation costs (e.g., fees to advisers, investment bankers, consultants, and due diligence checks required to identify and bid for suitable targets) and face negative repercussions from unsuccessful takeover bids[7]. In an environment where bidders have the option of selecting between alternative equally-suitable potential takeover targets, protected firms (i.e., firms in states with antitakeover amendments) as well as defensive firms (i.e., firms with pre-bid defence strategies and likelihood of staging a post-bid defence) are likely to face a lower takeover threat, all things being equal. In such a context therefore, a firm's takeover likelihood will not only depend on its observable financial (and related environmental) characteristics, but also on both the level of legal protection it enjoys (ϑ), its defences against takeovers (γ) and its perceived management-response to takeover bids (δ).

Some US studies (such as Espahbodi and Espahbodi (2003) and Cremers et al. (2009)) have attempted to capture these extra dimensions by including proxies for board behaviour when modelling the incidence of takeovers. For example, Cremers et al. (2009) include the governance index (G-index) developed by of Gompers et al. (2003) to capture the likely behaviour of firms faced with takeover threats[8]. The G-index has also been used in other US studies (see, for example, Cremers and Nair (2005), Masulis et al. (2007) and Ferreira and Laux (2007)) as a proxy for the level of antitakeover provisions (or takeover protection) within firms. Nonetheless, the index only captures two of three unknowns in equation 1.3.3(2) – the level of legal protection it enjoys (ϑ) and pre-bid defence strategies (γ). Post-bid defence strategies (such as ligation, solicitation of white knights, greenmail, standstill agreements, Pac-Man defence, employee stock ownership plans, share repurchases, recapitalisations, corporate restructuring, amongst others) are likely to have a greater impact as they constitute a tailored response by a target. Nonetheless, these post-bid responses cannot be reasonably modelled *a priori* with any level of accuracy, and are frequently assumed to be a stochastic error (albeit without justification).

Equation 1.2.3(1) clearly presents a simpler modelling framework if the research objective is to understand α_i – the characteristics of firms that make them susceptible to takeover

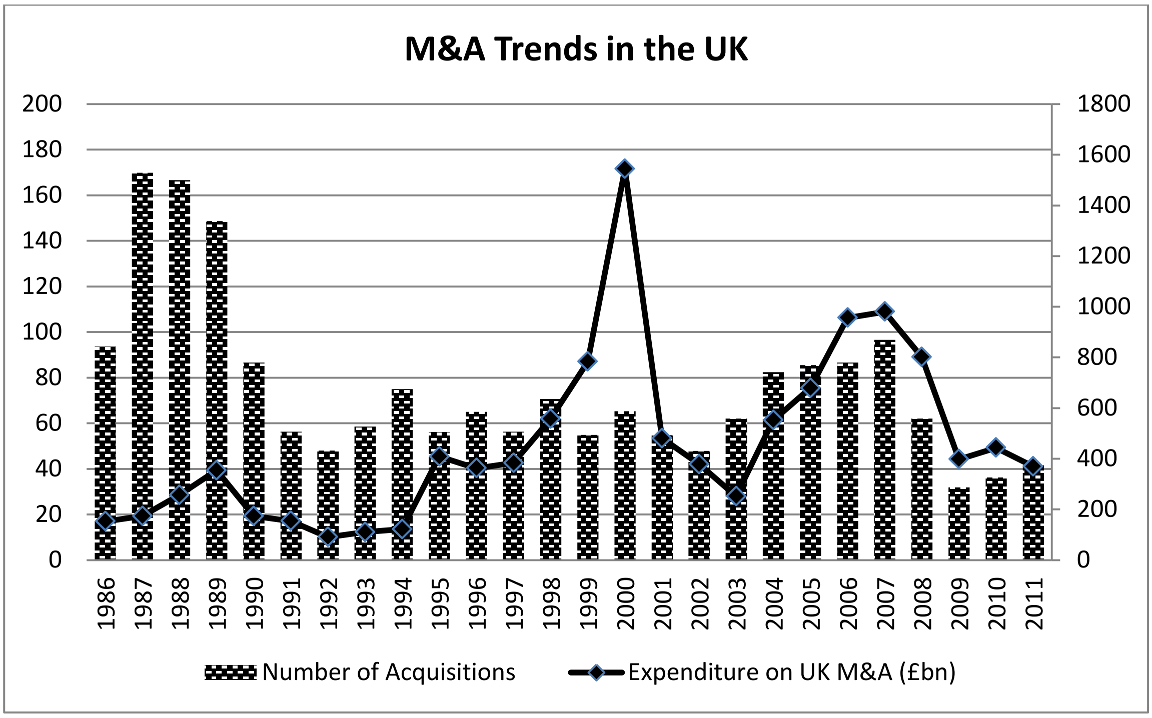
[7] Bradley et al. (1983), for example, finds that bidders in failed bids generate negative abnormal returns, particularly when the target is acquired by a rival bidder. Mitchell and Lehn (1990) also find evidence consist with an argument that managers are punished for poor acquisitions.
[8] Consistent with the argument in this section, Cremers et al. (2009) finds that a firm's takeover probability decreases when it has antitakeover provisions in its corporate governance framework.

bids. In this framework the relationship between P_i and α_i is free from the confounding effects of$\vartheta, \gamma_i, \delta_i$. I therefore argue that the UK potentially provides a cleaner context to understand this relationship. In section 1.3.4, I discuss some of the takeover trends in the UK. The objective of this discussion is to highlight both the level and the dynamism of takeover activity in the UK.

1.3.4 Takeover trends in the UK

The UK is one the world's most active takeover markets, only second to the US, both in terms of the number and the value of deals (Sudarsanam (2003)). Prior research reveals that an estimated 40% (or 33%) of UK listed firms between 1948 and 1970 (or between 1975 and 1990) were involved (as targets) in takeover activity (Dickerson et al. (2003)). This level of takeover activity is also corroborated by evidence provided by Sudarsanam (2003). This evidence shows that the second half of the 1960's saw an acceleration of merger activity which led to a first peak in 1968 (value of mergers; £1.95bn), a second peak in 1972 (value of mergers; £2.50bn) and a third peak in 1989 (value of mergers; £27bn). This indicates a substantial increase both in terms of number and value of mergers between 1968 and 1989. Merger activity in the UK continued to grow in the 1990s despite an initial slump in the early 1990's, with the growth in value outstripping the growth in number. The number and value of mergers grew by 28.75% (from 2,078 to 2,675) and 378.8% (from £47.2bn to £226.0bn), respectively, between 1989 and 2000 (Sudarsanam (2003)). Data from the Office of National Statistics (ONS, UK) shows that the growth in UK merger activity persisted between 2001 and 2007. Figure 1.3.4 shows trends in number and value of UK M&A between 1986 and 2011.

Figure 1.3.4: M&A trends in the UK between 1986 and 2011



Notes: Data on expenditure represents the sum of inward and domestic expenditure on M&A activity within the UK. All M&A activity (private and public) involving firms with value of £1 million or greater are considered. The data for this analysis is obtained from the UK Office of National Statistics online database (ONS (2012)). The left hand scale is the expenditure on UK M&A (in billions of pounds) and the right hand scale is the number of UK acquisitions. The expenditure on UK M&A is not adjusted for inflation.

The figure shows that the value of M&A has substantially grown over time despite a slight slump in the number of transactions. This can, perhaps, be attributed to the emergence of several mega-deals especially during the 1997–2000 dotcom boom. UK M&A slowed post-2000 but resurged after 2003 to another peak in 2007. The post-2007 decline in merger activity is generally attributed to the 2007 credit crunch and global financial crisis. This historical evidence highlights the active nature of the UK M&A market justifying why it presents a good case for M&A research. The sheer value of investment in UK M&A activity also highlights its importance to the investment community and to the economy as a whole.

1.3.5 Summary

This study employs a UK institutional context to pursue the research objectives. In this section (section 1.3), I discuss two main motivations for this choice. First, the UK has an active takeover market which (based on prior empirical evidence) is only second to the US. Second, unlike the US, the UK institutional and regulatory context allows for a better understanding (and modelling) of the relationship between a firm's characteristics and it takeover vulnerability. Overall, the UK provides a rich and clean context for understanding and modelling the firm-related factors that drive the takeover decision.

1.4 Contribution of the thesis

1.4.1 Overview

As noted in section 1.1, this thesis investigates four interrelated research issues including: (1) the determinants of target firms' takeover likelihood, (2) the extent to which targets can be predicted using publicly available information, (3) whether target prediction can form the basis of a profitable investment strategy, and – if not – (4) why investing in predicted targets is a suboptimal investment strategy. The Palepu (1986) model (together with the eight prediction hypotheses, noted in section 1.2) is used as a starting point. I build on this model by improving the underlying empirical methods and by increasing the set of predictive hypotheses to more fully capture the characteristics of takeover targets and enabling environments. The outcome is the development of an improved yet simple model which better explains the underlying reasons for target selection and which better allows users to predict what firms will be subject to takeover bids in the future. Overall, the thesis contributes in four main areas including: (1) characteristics of targets, (2) the takeover prediction modelling methodology, (3) investing in predicted targets, and (4) issues with predicted targets portfolios. These contributions are discussed below.

1.4.2 Characteristics of takeover targets

One of the objectives of this study is to expand our understanding of the characteristics of takeover targets by developing and testing new prediction hypotheses. I advance eleven new theoretically-grounded hypotheses for takeover prediction, which combine with the current (eight) hypothesis to provide a more comprehensive takeover target profile. These hypotheses are referred as 'new' because, to my knowledge, this is the first time the hypotheses are used in takeover prediction research. These new hypotheses are the: (1) firm size hypothesis, (2) firm capital structure hypothesis, (3) financial distress hypothesis, (4) firm lifecycle hypothesis, (5) M&A rumours hypothesis, (6) payroll synergies hypothesis, (7) share repurchase hypothesis, (8) asymmetric valuation hypothesis, (9) industry concentration hypothesis, (10) market liquidity hypothesis, and (11) market economics hypothesis.

Several of the new hypotheses borrow largely from existing hypotheses and theories in other areas of finance research. For example the new firm lifecycle, firm capital structure and firm size hypotheses are a simple extension of existing takeover prediction hypotheses. These hypotheses build on prior research (which employs firm size, leverage and firm age as predictors of takeover probability) but propose an alternative explanation for their relationship with takeover probability. Some of the hypotheses employ variables and proxies that have been extensively used in prior research (outside the area of takeover prediction). For example, HHI, residual volatility and a share repurchase dummy (proxies of industry concentration, asymmetric valuation and share repurchase activity) have been used extensively outside the takeover prediction literature. While the use of the spread between LIBOR and the Bank of England base rate as a measure of market liquidity is uncommon in the literature, it borrows from Harford (2005) – a US based study – which uses the spread between the commercial and industrial loan rates and the US Federal Reserve Funds rate as a measure of market liquidity.

These hypotheses are developed and fully discussed in chapter 3 (section 3.3) and are empirically tested in chapter 5. I find empirical evidence consistent with the newly proposed firm size, firm capital structure, payroll synergies, share repurchases, asymmetric valuation, industry concentration, market liquidity and market economics hypotheses. Overall, my results show that the new hypotheses, when added to the old hypotheses under a prediction framework, substantially improve the prediction model's classification and predictive ability.

1.4.3 Takeover prediction modelling

Besides the use of a limited set of hypotheses, there are several gaps, inconsistencies and biases in the methodologies employed in prior studies. These issues are highlighted here but are fully discussed in chapter 2. Prior studies have mainly employed matched-samples (i.e., equal number of targets and non-targets) in the development of the parameters of prediction models. This leads to significant survivorship bias as firms that are delisted, liquidated or go bankrupt are typically excluded from these samples. Further, prior studies employ arbitrarily selected test and holdout periods, with several studies employing a very short (usually one-year) holdout period. The results from such tests lack any generalisability.

Again, many studies focus on computing returns to predicted target portfolios but fail to test whether their models are able to predict actual targets. The latter is, perhaps, a more appropriate test of a prediction model's performance. The few studies that evaluate whether their model predicts actual targets compare model performance against poor benchmarks (such as a random selection prediction approach). Perhaps, a better benchmark for comparison is the performance of a control model. Most studies incorporate substantial look-ahead bias in their analysis by not recognising the time lapse between financial year-ends and the publication of financial results. The June approach (see Fama and French (1993) and Soares and Stark (2009)) is used in this study to substantially reduce this bias[9]. Last, prior studies typically use an arbitrarily-selected single method for identifying the optimal target portfolio from the holdout sample (e.g., the use of cut-off probabilities as opposed to deciles or quintiles).

In critique of these prior studies, I show that the results achieved by prediction models are a function of several of these methodological choices. The true predictive ability of these models can, perhaps, be observed only by averaging out the effect of methodological choices. I therefore employ a more robust framework for predicting takeover targets and testing prediction models by taking into consideration the issues raised above. In the empirical part of this study, I explore different portfolio identification techniques including deciles, quintiles, percentiles, cut-off probabilities (developed ex-ante) and fixed portfolios (of 100 firms, 50 firms, 30 firms and 10 firms). Further, I compare the performance of the new model against a control model (described as 'the old model') equivalent to the model used in prior studies. The choice of the control model allows any differences in performance between the two models to be directly attributed to one or more of the eleven new hypotheses.

The new takeover target prediction model developed in this study has a superior classification and predictive ability when compared with the control model (and when directly compared with results of prior researchers). These results are robust to the choices discussed above. The model's coefficients are reasonably stable and are, hence, useful for ascribing takeover probabilities to UK firms several years after coefficient development[10].

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[9] This approach allows a time lapse of six months between firm financial year end (assumed to be December for most UK firms) and the publication of firm financial data. This approach is fully discussed in section 4.2.5.

[10] I find that the performance of the model in out-of-sample testing does not systematically decline over a ten-year hold period.

The importance of such a model is the finding that, increasingly, studies use takeover probability as an independent variable in empirical research but the models used in these studies are, arguably naïve. The new model (together with its coefficient) can, perhaps, be useful to future researchers seeking to compute takeover likelihood for UK firms.

1.4.4 Investing in predicted targets

There is no consensus amongst prior researchers on whether investors can 'beat the market' by investing in portfolios of predicted targets. The results reported in several prior studies are also biased and lack generalisability due to some of the methodological issues highlighted in section 1.3.4. More importantly, to my knowledge, no prior study investigating this aspect, factors in the large losses that arise when predicted targets exit the market through bankruptcy and liquidation.

As one potential application of the new target prediction model, I evaluate the model's usefulness for investors seeking abnormal returns. I evaluate the model's performance across different estimation windows, portfolio holding periods, portfolio identification techniques and market cycles while taking into consideration the negative impact of firm exit through bankruptcy. I compare this performance against a control model (described as 'the old model') equivalent to the model used in prior studies. I find significant variation in the returns generated by the new model. The model generates high abnormal returns in some periods but also generates substantial abnormal losses in other periods. Consistent with the efficient market hypothesis, the long run return generated by the portfolios derived from the new model is not statistically different from zero.

In fact, the new model underperforms the old model in several cases. These results remain robust when periods of significant market decline (such as the dotcom crisis and the global financial crisis) are excluded from the analysis. This finding suggests a more fundamental problem with the strategy which is not explained by external market trends. The fourth contribution of this study is to investigate why takeover prediction using the new model is a suboptimal strategy despite the model's ability to correctly predict a high number of taker targets.

1.4.5 Why takeover prediction is a suboptimal investment strategy

Prior studies which find that target portfolios do not generate abnormal returns (e.g., Palepu (1986) and Powell (2001)) attribute this to market efficiency but fail to explain how market efficiency unfolds in this setting. For the first time, I empirically show that the suboptimal performance of predicted target portfolios can be explained by: (1) the presence of small poorly performing firms in the portfolios, (2) the tendency for predicted target portfolios to hold a number of firms which are declared bankrupt and earn –100% returns, (3) the mediocre performance of the large number of non-targets within the predicted target portfolios and its diluting effect on portfolio returns, (4) market anticipation of impending bids and its erosion of announcement period gains, and (5) the dynamics of target gains, annual portfolio rebalancing and the use of fixed portfolio holding periods. These five categories of issues combine to neutralise the abnormal returns to predicted target portfolios. This is discussed in greater detail in section 7.3.

1.4.6 Summary

This thesis seeks to contribute to the literature by investigating the unique characteristics of targets, the extent to which such characteristics can reliably predict future takeover targets, whether takeover target prediction can form the basis of a profitable investment strategy and (if not) why takeover prediction is a suboptimal investment strategy. The thesis also seeks to contribute to the literature by highlighting several sources of methodological biases in prior research and by proposing an improved framework for developing and testing target prediction models. Overall, I show that target prediction models can be improved through the introduction of relevant prediction hypotheses and improved empirical methods for prediction. A key output of the thesis is a relatively stable model which can better ascribe takeover probabilities to UK firms. This model is useful for key stakeholders such as regulators and management who may want to more fully understand the motivations underlying target selection or the likelihood that some firms will be subject to takeover bids in the future. Nonetheless, consistent with the market efficiency hypothesis, I find that if all known sources of bias are eliminated, there is no evidence that even an improved target prediction model can help investors to consistently 'beat the market' in the long run.

1.5 Structure of the thesis

The rest of the thesis is structured as follows. Chapter 2 is a literature review. The first section of the chapter highlights the relevance and underlying motivation for the research as well as its implications to theory development. The second part of the chapter looks at prior empirical research on takeover prediction, reviewing its development from early studies through to contemporary studies. A critique of these prior studies is carried out alongside, highlighting discrepancies, areas of weaknesses, unanswered questions and gaps in the literature. Chapter 3 starts with the development of takeover prediction hypotheses grounded in M&A theory. A theoretical literature review is used as the basis for the development of the prediction hypotheses proposed in the current study and developed in chapter 3.

The empirical part of the study starts with chapter 4, wherein the methodology for the study is developed and the data used in the study is discussed. The sample is analysed, preliminary descriptive statistics are presented and the method for outlier elimination is discussed. The hypotheses developed in this study are tested through univariate and multivariate analysis in chapter 5. Chapter 5 ends with the development of the new takeover prediction model. The model's classification and predictive ability are evaluated in chapter 6. In chapter 7, the ability of the model to be used as the basis of an investment strategy is evaluated. Further analysis is conducted in chapter 7 with a view to explaining some of the results obtained. The empirical findings from the study are summarised and the limitations of the study as well as its implications are set out in chapter 8.

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

This chapter discusses the underlying framework for takeover prediction modelling, as well as, the prior literature on the subject. Sections 2.2 and 2.3 discuss the relevance of predicting corporate events and the motivations for predicting takeover targets. Section 2.4 discusses the market anticipation and efficient market hypotheses and their implications on takeover prediction. Sections 2.5 and 2.6 critically review the empirical literature on takeover prediction modelling by looking at its development over the last 60–70 years. The next section is an overview of the literature on predicting corporate events. It sets the stage for discussing the motivation of this study.

2.2 The prediction of corporate events: An overview

Mueller (1972) presents a framework to describe the typical lifecycle of a firm. Mueller's postulation highlights the tendency for firms to experience several key events over their life time. These defining events (such as initial public offerings, acquisitions, bankruptcies and liquidations, amongst others) are generally of interest to stakeholders. Understanding why these events occur and even predicting whether these events will occur at some point in the future has, therefore, been of interest to both researchers and practitioners. The basis for the prediction of corporate events is the assumption that certain events that occur during the lifetime of an organisation do not occur randomly but are driven by observable factors. The task of predicting these events starts with understanding the factors that drive them, as well as, their underlying dynamics.

Prediction of corporate events as a research area in finance is, perhaps, pioneered by Altman (1968) which develops a model to predict firms that are likely to go bankrupt. Altman (1968) uses key accounting variables such as retained earnings (RE), total assets (TA), earnings before interest and taxes (EBIT), working capital (WC), market value of equity (MV), book value of total debt (BV) and sales (S), to identify firms with a high likelihood of becoming insolvent. The dynamics between these variables is explored in his study, through the use of five financial ratios including WC/TA, RE/TA, EBIT/TA, MV/BV and S/TA. The area of bankruptcy prediction has been advanced through the development of more advanced bankruptcy prediction models. Key contributions in the bankruptcy prediction literature have been made by Altman et al. (1977), Ohlson (1980), Taffler (1984), Shumway (2001), and Agarwal and Taffler (2008), amongst others. The growth of this literature is backed by the increasing need for policy makers, management and investors to understand the factors that drive firms towards insolvency and to quantitatively measure the risk that a firm might go bankrupt in the future.

Like bankruptcy, the occurrence of takeovers, the characteristics of firms engaged in takeovers and the measuring of takeover exposure of firms, are issues of interest to corporate stakeholders, notably, policy makers, management and investors[11]. In line with the bankruptcy prediction studies, takeover prediction studies use accounting variables and financial ratios such as return on assets, total assets, market capitalisation, leverage ratio, market to book value and price to earnings ratio to develop models for the prediction of future merger candidates (targets and bidders). Prior studies such as Hayes and Taussig (1968), Vance (1969), Monroe and Simkowitz (1971), Belkaoui (1978), Palepu (1986), Ambrose and Megginson (1992), Powell (2001), Espahbodi and Espahbodi (2003), Brar et al. (2009) and Cornett et al. (2011) have advanced the literature through the development of indicator variables and the refinement of initial prediction models. An overwhelming majority of the studies have focused on the prediction of merger targets with just a few studies (such as Cornett et al. (2011)) attempting to predict bidders. This is, perhaps, due to the fact that the motivations for predicting targets (discussed in section 2.3) are more compelling.

Other events and issues which have also attracted some interest in the prediction literature include: share repurchases (e.g., Dittmar (2000)), credit ratings and credit rating changes (e.g., Pinches and Mingo (1973) and Laitinen (1999)) and loan decisions by loan officers (e.g., Libby (1975)) and Dietrich and Kaplan (1982)). The event of interest in this study is takeovers. More specifically, the current study develops a model to predict future takeover targets. While such a model is useful in its own rights (as will be discussed in section 2.3), the study goes further to explore whether the model can be used as a tool for investment decision-making. The next section (section 2.3) discusses the usefulness of takeover prediction modelling to different stakeholders – the motivation for the study.

[11] The relevance of these issues to the different stakeholders is discussed in section 2.3.

2.3 The relevance of takeover prediction modelling

2.3.1 Overview

The decision to focus this study on developing takeover target prediction models is driven by the continuing relevance of the issue to different stakeholder groups and the apparent inconsistencies and gaps in the current literature (further discussed in section 2.6). The key stakeholders with an interest in takeover activities include: corporate management, investors, and policy makers. The relevance of takeover prediction modelling to these key stakeholders is discussed in sections 2.3.2 to 2.3.4. Besides its direct relevance to these key stakeholders, merger and acquisition activity provides a useful research context for standard setters and business researchers. These issues are discussed in sections 2.3.5 and 2.3.6 respectively.

2.3.2 Relevance to management

The employment effects of M&A on target managers, as well as, the tendency for target managers to, typically, be ousted during the integration phase of M&A, is well documented in the literature (Cannella and Hambrick (1993) and Hartzell et al. (2004)). In many circles, a takeover is viewed as a sign of target management inefficiency (further discussed in chapter 3). Being able to anticipate future takeover bids is therefore important to the management of potential target firms who may want to take action to safeguard the interests of their shareholders (the neoclassical perspective – Ruback (1987)) or extract excess managerial rent (the managerial perspective – Willcox (1988)).

In contexts wherein the use of some takeover defence strategies is legally appropriate, knowledge of takeover risk can allow managers to set up applicable pre-bid or post-bid takeover defence strategies. These defensive strategies can either make the firm unattractive as a potential target, or may even allow target management to generate a higher takeover premium for their shareholders (Ruback (1987), Holl and Kyriazis (1997), Schwert (2000) and Klock et al. (2005))[12]. Further, knowledge of the likelihood that a firm's competitors and supply chain partners will engage in M&A activity is, perhaps, important for the firm's long term strategy development.

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[12] Klock et al. (2005), for example, note that managers in threat of takeovers react by distributing excess cash, increasing their pay-outs to shareholders, typically recapitalize their firms, and may focus firms through spinoffs and divestitures. Ruback (1987) contends that managers resist takeovers for three main reasons; '(1) they believe the firm has hidden values, (2) they believe resistance will increase the offer price and (3) they want to retain their positions' (p. 50).

2.3.3 Relevance to investors

Corporate events such as takeover and bankruptcy announcements usually result in significant price movements. The motivation of several target prediction studies is that the ability to identify potential takeover targets in advance of the bid announcement can be a basis for a successful investment strategy (Palepu (1986), Powell (2001) and Brar et al. (2009)). There is consensus within the events studies literature that takeover targets gain substantially from takeover activities. Research has consistently documented substantial excess return accruing to targets (e.g., Jensen and Ruback (1983), Frank and Harris (1989), and Georgen and Renneboog (2003)) and insignificant returns or significant losses to bidders (e.g., Franks and Harris (1989), Stulz et al. (1990) and Danbolt (1995)).

Jensen and Ruback (1983), summarising results from previous short run event studies on target gains (including Dodd and Ruback (1977), Bradley et al. (1983) and Ruback (1983)), show that targets in the US gain between 16.9% and 34.1% abnormal returns, with the weighted average gain amounting to 29.1%, in the months surrounding merger announcements. Using a large sample of 1,898 targets, Franks and Harris (1989) show that UK targets gain over 25.0% abnormal returns in the five-month period starting four months prior to the takeover announcement (month –5) and ending one month after the announcement (month +1). This evidence of significant gains to UK targets is corroborated by Georgen and Renneboog (2003) and Danbolt (2004)[13]. These results are robust to moderating factors including the bid characteristics.

Investors can, perhaps, generate substantial abnormal returns if they are able to successfully predict future target firms. Jensen and Ruback (1983) contend that there are always a series of occurrences or cues that increase or decrease the probability that a firm will become a target of a takeover. These cues are likely to be picked-up by other market participants and hence reflected in share prices. Consistent with this argument, Keown and Pinkerton (1981) find that over half of the abnormal returns that accrue to targets of takeovers are earned prior to the actual announcement day. This suggests that the challenge faced by an investor (relying on takeover prediction) is not only to identify future targets a few months before they become the subject of an announced takeover bid but also to do so

[13] Georgen and Renneboog (2003) find that UK targets gain cumulative abnormal returns of 29.0% between month –2 and +2 relative to the bid. Similarly, Danbolt (2004) shows that UK targets of domestic bidders earned cumulative average abnormal returns of 24.37% over month –2 to month +1 relative to the bid, while UK targets of foreign bidders earned cumulative average abnormal returns of up to 31.35% in the same period.

before other market participants. Aside from errors in prediction, buying-in too early is another potential risk which such an investor might face. As several studies (e.g., Morck et al. (1988) and Asquith (1983)) have shown, on average, targets underperform in the period before they are acquired.

Overall, prior empirical evidence suggests that investors can, potentially, generate substantial abnormal returns from takeover prediction modelling. This is however, not a straight forward process as a lack of precision in prediction (such as getting the timing wrong and predicting firms which do not eventually receive takeover bids) might erode any potential gains to be made. As will be shown in section 7.4, there are other significant risks involved, particularly the risk of predicting and investing in firms that eventually file for bankruptcy.

2.3.4 The policy and legal perspective

The UK Financial Service Authority (FSA) has continuously sought to discourage and eliminate insider trading or market abuse in the UK financial market. This is the objective of the Financial Services and Markets Act 2000 (FSA (2000)). The preservation of an orderly market in the shares of bidders and targets through effective disclosure is also a prime ethos of the takeover code[14] administered by the UK Takeover Panel. This is covered in Rule 2 of the code (Takeover Code (2011)).

Keown and Pinkerton (1981) note that takeovers are poorly held secrets as the takeover process generally involves several groups and individuals (e.g., investment bankers, advisers, management) all of whom generally hold material price-sensitive information not in the public domain. Events studies on takeovers (including Keown and Pinkerton (1981), Franks and Harris (1989), and Danbolt (1995), amongst others) show that target share prices start rising up to four months before the bid announcement. Keown and Pinkerton (1981) attribute this growth in prices and the corresponding increase in trading volume to information leakage and insider trading activity. In contrast, Jensen and Ruback (1983) attribute the price run-up to the market's anticipation of imminent bids.

Market regulators have a general duty to investigate, on a case by case basis, whether such price run-ups are due to insider trading activity or market anticipation. To date, the literature focuses on testing the insider trading hypothesis, perhaps, because market

[14] The code was last amended in September 2011.

anticipation is non-observable. Prediction modelling provides regulators with a tool to investigate the extent to which some takeover targets could have been anticipated by market participants using only publicly available information. The results from such analyses could inform decisions on whether (or not) to investigate potential cases of market abuse. An example of this analysis is conducted in section 7.3.4.

Further, M&A activity impacts on economic prosperity as it underlies economic growth, industry competition, employment and general welfare. The regulation of M&A activities is, therefore, an important duty of regulators and policy makers. Takeover activity in the UK is regulated by the takeover code which is periodically amended. Policy changes might directly have one of two effects on potential target firms – it can either increase or decrease the likelihood of firms to be acquired. A protectionist policy, for example, can, ceteris paribus, reduce the likelihood of firms being acquired over time and vice versa. Measuring the impact of changes to the code is, possibly, of interest to policy makers. The case of the impact of the 2011 change to the takeover code, for example, has been discussed in both academic and policy circles. The ensuing debate and the potential role of takeover prediction modelling in this debate are briefly discussed below.

The amendments to the UK takeover code introduced by the Takeover Panel in September 2011 have been viewed as a response to the widely criticised takeover of Cadbury by Kraft[15]. The UK takeover code has traditionally sought to facilitate takeover activity and protect target shareholders by preventing target management from adopting frustrating tactics (such as takeover defences). The current UK takeover code, perhaps, empowers management, by giving management more control of the deal process. To date, it appears the effects of this change of focus from a shareholder perspective to, perhaps, a stakeholder perspective are not fully understood. Given that the UK has traditionally been viewed as the largest M&A market outside the US, the takeover panel is, possibly, keen on ensuring that new changes to the code do not inhibit merger activity. Takeover prediction modelling

[15] The Takeover Panel argues that these changes to the Code are designed to increase transparency in the offer process, improve the quality of disclosures, recognise the interests of target employees, emphasise the power of the target's board in communicating deal merits, and protect targets by prohibiting deal protection and inducement fees. Amongst others, notable changes in the code include: the prohibition of break fees and deal protection measures, a requirement for all known potential bidders to be publicly identified, a 'put-up or shut-up' rule requiring bidders to make a firm offer or withdraw within 28 days of being publicly identified and a requirement to disclose details of how the proposed takeover will be financed (see Takeover Code (2011)).

provides an empirical way of testing whether policy changes have an impact on takeover likelihood and hence, overall activity[16].

2.3.5 Investigating the value-relevance of accounting information

Watts and Zimmerman (1978, 1986, 1990) argue that the role of positive accounting research is to develop theory that can explain observed phenomena or occurrences[17]. The decision model paradigm (Belkaoui (1996)) and the events approach (Sorter (1969)) of accounting theory are both centred on the provision of information about relevant economic events and the development of appropriate models that may be useful in explaining and predicting such events. The decision model paradigm prescribes that the appropriate choice of an accounting method and the quality of accounting measurements should be judged based on the predictive ability of the information generated (Beaver et al. (1968, 1996))[18]. This is also consistent with Bartley and Boardman's (1990) contention that the usefulness of accounting information can be directly evaluated by their ability to help investors predict future events.

As noted in section 2.2, several research papers focus on using financial statement information to predict corporate events and outcomes. Some key studies (such as Walter (1994) and Bartley and Boardman (1986, 1990)) have explicitly used takeover prediction models as a framework to test the usefulness of accounting data. Bartley and Boardman (1986) test whether the ratio of market value to inflation-adjusted book value is better able to classify targets than the ratio of market value to historical book value. The study finds that prediction models with inflation-adjusted financial ratios are better able to classify targets and non-targets when compared to prediction models that employ only historical cost ratios. They conclude that inflation adjusted accounting data is more value-relevant to users when compared to historical cost accounting data[19]. Walter (1994) also investigates

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16 This can, potentially, be achieved by evaluating the change in UK firms' probability of being acquired across two different time periods – pre and post policy change (i.e., whether policy change constitutes a breakpoint in the model. This can also be investigated by testing whether policy change (proxied by a dummy variable) can explain takeover likelihood.

17 In fact, Watts and Zimmerman (1986) stated that, '…the objective of accounting theory is to explain and predict accounting practice' (p. 2). Deegan and Unerman (2006) contend that the prediction of events and explanation of phenomena are at the core of positive accounting research.

18 As Beaver (1966) reiterates, the premise here is that, 'accounting data can be evaluated in terms of their utility and that utility can be defined in terms of predictive ability' (p. 99).

19 Bartley and Boardman (1990) build on their earlier study by testing whether inflation-adjusted accounting information is more useful than historical cost accounting information. The researchers achieve this by developing and comparing the performance of two different models – one with inflation adjusted data and the other with historical cost information. In line with earlier studies,

the usefulness of current costs accounting data (replacement costs) by testing whether target prediction models developed with such accounting data can be useful to investors[20].

The UK, like other countries, has been subject to several changes in accounting regulations (i.e., International Financial Reporting Standards) issued by the International Accounting Standards Committee (between 1973 and 2001) and the International Accounting Standards Board (after 2001). The IFRS has generally promoted the use of several cost measurement methods including historical costs, net realisable value (residual value), current cost, present value (entity-specific value) and fair value, depending on the asset in question and how it was acquired (Alexander et al. (2007))[21]. Alexander et al. (2007) note that the IFRS (as opposed to the US GAAP) is still predominantly principle-based (as opposed to rule-based), allowing UK managers some flexibility in choosing an appropriate cost measurement method for different assets. In line with the works of Beaver (1966), Sorter (1969), Bartley and Boardman (1986, 1990) and Walter (1994), takeover prediction modelling can, perhaps, provide a useful framework for the investigation of value-relevance of different accounting choices and accounting information for investors.

2.3.6 Takeover probability – An explanatory variable in empirical research

Another interesting area of development and usefulness of takeover prediction and modelling of takeover probability is its use as an explanatory variable in empirical research. Recent studies such as Cornett et al. (2011), Bhanot et al. (2010) and Cremers et al. (2009) investigate new research questions by employing firm takeover risk as a main explanatory variable in their research design. These studies are fully discussed in section 2.5.6[22]. The underlying assumption across the three studies is that their models for

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Bartley and Boardman (1990) confirm that inflation adjusted data is value-relevant as it improves the classification ability of prediction models.

20 Walter (1994) shows that current cost models improve the explanatory power of prediction models.

21 As will be discussed in chapter 4, the current study does not use inflation adjusted data or current cost information as this information is not available for all firms over the sample period.

22 Cornett et al. (2011) investigate investors' anticipation of bidder and target candidacy in takeovers and whether this anticipation moderates the wealth distribution between bidders and targets in takeovers. In the research design, the likelihood of a firm becoming a target or a bidder are used to develop a surprise instrument (a measure of market anticipation). Bhanot et al. (2010) study the effect of a firm's takeover risk on the relationship between its stock returns and bond prices. They show that highly rated firms with a high takeover likelihood have a more positive correlation between their stock returns and bond spreads, and vice versa. Cremers et al. (2009) develop a model to determine firm takeover likelihood. They show that a takeover factor (derived

measuring takeover risk is adequate, correctly specified and fully capture the concept of takeover risk. As will be discussed further, these studies, potentially, employ suboptimal models for computing and ascribing takeover probability[23]. This is, perhaps, because modelling takeover likelihood is not the primary objective of these studies. This thesis seeks to address this issue through the development of a new takeover prediction model (together with model parameters) which can, perhaps, be adopted by future researchers.

2.3.7 Summary

This section has discussed the importance of takeover prediction modelling by reviewing current research and practice in different areas. It is shown that takeover prediction modelling can provide a useful tool for managers evaluating their risk of being acquired, investors seeking above market returns, regulators unearthing the reasons for pre-bid price run-ups, policy makers evaluating the impact of their policies on M&A activities, and researchers exploring new research questions. The current study aims to provide a more efficient yet simple to use takeover prediction model which can potentially assist these different stakeholders. The next section discusses two key theoretical concepts with implication to takeover prediction modelling.

2.4 Market anticipation and efficient market hypotheses: Implications for prediction

Takeover prediction modelling has direct implications for the efficient market hypothesis (EMH) as prediction models rely on publicly available accounting information. The semi-strong form EMH posits that such information cannot be used by investors to identify assets (e.g., future targets) from which abnormal returns can be consistently earned (Fama (1970)). This suggests that takeover likelihood, for example, is continuously factored into share prices upon receipt of new information. Hence, investing in a portfolio of predicted targets (irrespective of whether these predicted targets eventually receive a bid) should not generate excess returns.

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from takeover spread portfolios) is able to predict the level of takeover activity in the economy and explained the abnormal returns to governance-based (G-index) spread portfolios proposed by Gompers et al. (2003).

[23] The impact of these suboptimal models on the results and conclusions of these studies is not easily discernible.

Nonetheless, prior evidence suggests that investors are unable to accurately predict future targets (Jensen and Ruback (1983))[24]. Hence, share prices are unlikely to fully reflect takeover likelihood. Prior studies attribute the inability to generate abnormal returns from predicted target portfolios to the difficulty of predicting takeover targets (see Palepu (1986), Barnes (1998, 1999, 2000) and Powell (2001)). These studies argue that this finding – the inability to generate abnormal returns from predicted target portfolios – lends support to the EMH. Given some of the weakness of these prior prediction models, it is unclear whether the poor performance of the portfolios is a due to the inadequacy of the prediction models or the market's ability to anticipate impending bids. This is further discussed in section 7.3.

Event studies in M&A mainly use the price reaction to takeover announcements as a test of market efficiency (see Asquith (1983)). These studies consider the significant price reaction at the time of bid announcement as a signal of market efficiency. As will be shown in section 7.3.4, a non-significant price reaction at the time of announcement is consistent with market efficiency if the market is able to fully anticipate the event. Other studies use pre-bid price run-ups as evidence of insider trading (e.g., Keown and Pinkerton (1981)). As will also be shown in section 7.3.4, a pre-bid price run-up will not reflect insider trading if the market is able to partly anticipate the event. In the two cases, share prices will adjust continuously to incorporate the likelihood of an event occurring in the future. This suggests that tests of market efficiency focusing on M&A, perhaps, need to control for the level of market anticipation.

Further, short run event studies examining the returns to takeover targets and bidders, frequently, undermine the importance of market anticipation of these events. The level of market anticipation for each target can be gauged by computing the target's pre-bid takeover probability. This study extends prior literature by testing the EMH in the context of takeover prediction. This context allows for the effect of market anticipation to be controlled (e.g., by comparing the returns to targets with a high takeover likelihood to targets with a low takeover likelihood). This context also permits further investigation of how the EMH unfolds. This is further discussed in section 7.3. The next section reviews prior research on takeover likelihood modelling.

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[24] Jensen and Ruback (1983) note that, '…it is difficult, if not impossible, for the market to identify future target firms' (p. 29). The recurrent finding that targets earn significant abnormal returns on the announcement day further suggests that the market only poorly anticipates impending bids.

2.5 Empirical literature on takeover likelihood modelling

2.5.1 Overview

The previous sections (2.3 and 2.4) have highlighted the relevance of takeover prediction modelling to stakeholders (such as management, investors, regulators and policy makers) and to the development of finance theory. The goal of this section is to present a summary of key studies on takeover prediction modelling. Hayes and Taussig (1968) and Vance (1969) are amongst the earliest studies in takeover likelihood modelling. These studies use discriminant analysis to identify the unique financial characteristics of takeover targets. A major shift in the literature is introduced by Palepu (1986). This paper introduced several methodological advancements which have been adopted in the literature. As will be discussed, this paper has remained a key source of reference with more contemporary studies adopting the methods introduced in Palepu (1986).

With increased technological developments, a new stream of studies has emerged over the last decade. These studies explore different modelling techniques such as Artificial Neural Networks, Decision Trees, Support Vector Machines, Fuzzy sets, Multi-Criteria Classification Techniques and other Machine Learning models. Other studies have simply tailored 'the Palepu approach' to different datasets while adjusting for other sample specific characteristics.

As will be discussed in section 2.5.5, investment firms and practitioners (such as Morgan Stanley and Deutsche Bank, amongst others) have also been engaged in takeover prediction as an investment strategy. To support this review, the prediction of takeovers in practice is also summarised albeit from a limited set of published material. Another interesting development in the literature is the emergence of new studies post-2009 using takeover probability as an explanatory variable in empirical research. Some of these studies will also be reviewed in section 2.5.6.

Three major research streams have emerged over time. The first looks at improving our understanding of the characteristics or profile of takeover targets and the factors that make certain firms attractive to bidders[25]. The second stream of studies focuses on developing predictive models and employing different empirical techniques to improve the accuracy of

[25] Hasbrouck (1985), for example, looks at how firm characteristics such as size, leverage, liquidity and Tobin's Q differ between targets and non-targets. Other examples of studies under this stream are included in table 2.5.1.

target prediction[26]. The third stream focuses on assessing whether takeover prediction models can be used to generate abnormal returns for investors. Table 2.5.1 summarises the key papers in the areas, highlighting their period under study, the context or sample choice and the stream or focus of the research.

Table 2.5.1: Prior studies on takeover prediction

Study	Period	Context	stream
Simkowitz and Monroe (1971)	1968	USA	M
Stevens (1973)	1966	USA	C
Belkaoui (1978)	1960-1968	CAN	C, M
Dietrich and Sorensen (1984)	1969-1973	USA	C
Hasbrouck (1985)	1977-1982	USA	C
Bartley and Boardman (1986)	1978	USA	C, M
Palepu (1986)	1971-1979	USA	C, M, I
Barnes (1990)	1986-1987	UK	C, M
Bartley and Boardman (1990)	1975-1981	USA	C
Ambrose and Megginson (1992)	1981-1986	USA	C
Walter (1994)	1981-1984	USA	M, I
Powell (1997)	1984-1991	UK	C, M
Barnes (1999)	1991-1993	UK	M
Barnes (2000)	1991-1993	UK	M
Powell (2001)	1986-1995	UK	M, I
Espahbodi and Espahbodi (2003)	1993-1997	US	M
Powell (2004)	1986-1985	UK	M, I
Powell and Yawson (2005)	1986-2000	UK	C
Powell and Yawson (2007)	1992-2002	UK	C, M
Brar et al. (2009)	1992-2008	EU	C, M, I
Cremers et al. (2009)	1981-2004	USA	M
Bhanot et al. (2010)	1980-2000	USA	M
Cornett et al. (2010)	1979-2004	USA	M
De and Jindra (2012)	1980-2006	USA	C

Notes: Context: CAN- Canada, USA- United States, UK- united Kingdom, Stream: C-characteristic, M- prediction modelling, I-Investment opportunity. The studies are listed based on the date of publication with the earliest studies at the top of the table.

Given the broad nature and long history of the research area, a historical perspective is adopted in this review. Here, the studies are discussed based on the era during which they are published. While not clearly distinct from each other, three key eras are identified for discussion purposes. These eras span 1968–1985 (first era), 1986–2002 (second era) and 2003–2013 (third era). The basis for this classification is the realisation that studies

[26] For example, Palepu (1986) highlights the importance of methodology and proposes improvements on the methodologies employed in earlier studies. Other researchers such as Barnes (1998) and Powell (2001) have also raised related methodological issues. Advances in computer technology have allowed some researchers such as Espahbodi and Espahbodi (2003) to explore the usefulness of other models such as artificial neural networks in the prediction of takeover targets.

published during each of these three eras share significant similarities in their approach and their methodologies. These similarities will be further discussed in sections 2.5.2 to 2.5.4. Within these eras, the studies are further sub-classified based on the context or country employed. These will allow the results of this thesis (which focuses on the UK context) to be effectively reconciled with previous empirical research bearing in mind any contextual differences. Section 2.5 provides a historical and contextual overview of related prior studies. Section 2.6 integrates the studies from the different eras and contexts and provides a critical evaluation of the methodologies and conclusions of these studies. Section 2.6 also discusses the ways in which the current study improves upon the weaknesses of prior studies.

2.5.2 Empirical studies in takeover prediction 1968–1985

2.5.2.1 Overview

Most of the empirical work during the 1968–1985 era focuses on the US context. Few studies during this era focused on other markets such as the UK, Canada and the rest of Europe. This section discusses the contributions of the key US and UK studies during this era.

2.5.2.2 US studies

As noted above, Hayes and Taussig (1968) is, perhaps, the earliest study on takeover prediction modelling. The objective of Hayes and Taussig (1968) is to investigate whether firms which failed to provide sufficient information to investors are more likely to be acquired. The researchers investigate whether the choice of accounting policy used by firms can affect their probability of being acquired. On a US sample of 50 targets and 50 non-targets between 1956 and 1967, Hayes and Taussig employ univariate analysis on a set of accounting variables[27] to show that accounting policies employed – specifically over-conservative accounting policies – do not increase a firm's likelihood of being acquired. They note that, instead, poor investment policies[28], a low return on net worth, and a declining (or unpredictable) dividend pay-out, are features of takeover targets.

Following on from Hayes and Taussig (1968), Vance (1969) develops a raider's index[29] based on financial statement variables. Vance asserts that, '…management should realise;

[27] These accounting variables included inventories to total assets, net fixed assets to total assets and book value to market value.
[28] In this study investment policies are proxied by excess liquid assets.
[29] The raider's index is a list of potential target firms.

many (if not all) of the takeovers or tenders can be foreseen by looking at the victim's (target's) published financial data' (p. 93). The objective of this index was, therefore, to provide guidance to management on the likelihood of being the subject of a takeover. Vance (1969) identifies four variables[30] that are 'principal indicators of the degree of corporate vulnerability to a takeover attempt' (p. 94). In a holdout sample of 21 actual target firms (and no non-target firms), Vance's index is able to correctly highlight 17 as potential targets.

Monroe and Simkowitz (1971) seek to improve upon the methodology of earlier studies through their use of stepwise discriminant analysis and a broader set of financial variables. They employ discriminant analysis based on 24 firm financial characteristics on a sample of listed US firms in 1968 with the objective of discriminating between future targets and non-targets. They observe that future targets and non-targets can be distinguished on the basis of both their financial and non-financial characteristics. They conclude that acquired firms have a lower PE ratio, paid out lower dividends, experienced low growth in equity and are generally smaller in size.

The use of stepwise discriminant analysis in Monroe and Simkowitz (1971) appears to have paved way for methodological criticisms and development in the area. An example is the application of factor analysis (by Stevens (1973)) – a variable reduction technique which is, perhaps, more theoretically robust when compared to stepwise analysis. Stevens (1973), using factor analysis and multiple discriminant analyses, finds that future targets and non-target firms can be distinguished from each other based on their financial characteristics. Stevens employs an equal sample of 40 targets and 40 non-targets from US publicly listed firms in 1966 to show that targets have lower leverage, lower profitability and higher liquidity. Stevens (1973) concludes that, '…financial characteristics either are explicit decision variables or directly reflect non-financial reasons for acquisitions' (p. 157).

Wansley et al. (1983) do not set out to predict future targets per se, but to investigate whether firms with a high degree of resemblance to acquired firms earn abnormal risk-adjusted returns[31]. They employ discriminant analysis and a broad set of firm accounting

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30 These variables include liquidity, debt position, price earnings ratio and stability of earnings.

31 The motivation for this study is a periodic publication of a list of potential 'Acquisition Candidates' by the brokerage firm, E.F Hutton, coupled with the knowledge that merger targets earned significant abnormal returns.

and market variables[32] to derive models that discriminate between acquired and non-acquired firms. By holding a portfolio of 25 firms with target characteristics, Wansley et al. (1983) show that cumulative abnormal returns of up to 17.1% can be generated over a 21 month holding period[33]. Aside from significantly expanding the set of potential discriminatory variables in target prediction studies, this study was one of the first to highlight the possibility that a portfolio of firms with semblance to merger targets might generate abnormal returns for investors.

2.5.2.3 UK Studies

Singh (1971) is, perhaps, the earliest study investigating the unique financial characteristics of UK targets. Singh (1971) employs univariate and discriminant analysis on a sample of 847 UK firms which operated between 1954 and 1960[34]. Singh finds that, when compared with non-targets, UK targets have lower profitability, lower growth and lower valuation ratios.

Tzoannos and Samuels (1972) build on the work of Singh (1971) by investigating the differences between the characteristics of UK targets and UK bidding firms. Tzoannos and Samuels (1972) use a sample of 36 mergers (targets and bidders) and a control sample of 32 non-merging firms between 1967 and 1968[35]. Their analysis reveals that UK targets have high levels of capital, experienced a growth in gearing and a decline in profits, have low P/E ratios, have low dividend growth rates and were inconsistent in their dividend pay-outs. Bidders on the other hand, have low levels of capital and reported falling gearing ratios, growing dividends and growing profitability.

Keuhn (1975) extends Tzoannos and Samuels (1972) by employing a longer sample period from 1957 to 1959 and linear probability and probit models to investigate the

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[32]The variables used in the study represented 10 dimensions of a firm's financial profile and its market characteristics including: profitability, size, leverage, age, liquidity, price-earnings, stock activity, market valuation, growth, turnover, and dividend policy.

[33] The CAR to the top 50 firms is indifferent from zero and none of the top 50 firms is involved in M&A activity in 1977 – the year of study. Nonetheless, 12 of the top 50 firms are involved in M&A activities within the next 3 years (1979-1980).

[34] The study employs financial variables such as return on capital employed, return on equity and return on assets (as measures of profitability), dividends to equity ratio (as a measure of dividend return), net profit to financial capital employed (as a measure of productivity return), current assets to total assets (as a measure of liquidity), long term liability to total capital (as a measure of gearing), net assets (as a proxy for firm size), percentage change in net assets (as a proxy for growth), and market to book value of equity (as a measure of firm valuation).

[35] The study uses discriminant analysis to distinguish targets from non-merging firms and bidders from non-merging firms across five main dimensions. These dimensions include: capital structure, profitability, liquidity, investment and dividend policy.

characteristics of UK targets and bidders. Keuhn (1975) finds that UK targets are characterised by low valuation ratios, profitability ratios, liquidity levels and growth. UK bidders on the other hand, have high valuation ratios and growth levels but low profitability ratios when compared to their industry average (Keuhn (1975)).

2.5.2.3 Summary

The review above has summarised some of the key US and UK studies in the 1968–1985 era of takeover prediction. Other studies in this era looking at characteristics of takeover targets include Rege (1984) and Belkaoui (1978) – employing a Canadian sample – and Dietrich and Sorenson (1984) and Hasbrouck (1985) – employing a US sample – amongst others. Overall, the studies in this era establish that a profile for targets can potentially be built as targets share some common characteristics. Irrespective of context (US or UK), most of the studies seem to agree that targets are characterised by low valuation ratios (i.e., targets are potentially undervalued firms), unstable or falling dividends and low profitability ratios (i.e., targets are, on average, poorly performing firms). The studies also establish that financial and market variables can act as reasonable proxies for the motives of takeovers. Aside from their methodological weaknesses (as critiqued by Palepu (1986) and discussed in section 2.5.3.2), these studies fail to provide a theoretical framework underlying the selection of variables in the models. The studies neither discuss the choice of discriminatory variables nor hypothesise on the relationship between variables and takeover likelihood.

2.5.3 Empirical studies in takeover prediction 1986–2002

2.5.3.1 Overview

There appear to have been a decline in the number of studies looking at takeover prediction during the 1986–2002 era when compared with the first era. Fewer USA studies, in particular, focused on takeover prediction. This decline can, perhaps, be attributed to Palepu's (1986) seminal study which concluded that, when the analysis is done appropriately, takeover prediction, especially for investment purposes, is an unattainable goal. The Palepu (1986) study presents a detailed critique of studies in the first era. This critique is summarised in this section. During this era (1986–2002), other key contributions to the literature have been made by UK studies such as Barnes (1990, 1999, 2000) and Powell (1997, 2001). To the best of my knowledge, much less has been published for other regions such as Canada, Australia and the rest of Europe. This section discusses some of the contributions of the key US and UK studies during this era.

2.5.3.2 US studies

Palepu (1986) is considered a seminal study in the area and has been recurrently cited in contemporary studies. The main contribution of this paper is that it brings to light some methodological biases in earlier (1968–1985) takeover and bankruptcy prediction studies and proposes an improved method for modelling takeover risk. Palepu (1986) raises three key weaknesses in prior research methodologies, including (1) the use of non-random equal-share samples in model estimation, (2) the use of arbitrary cut-off points in target prediction, and (3) the use of equal-share samples in prediction tests. These issues are discussed below.

i.) Non-random equal-share samples or state-based sampling methodology

The fact that M&A are rare events (within the population of firms) is generally perceived as an obstacle to prediction modelling. For example, as will be discussed in section 4.2, only 5.28% of all UK listed firms, on average, receive takeover bids each year during the sample period of this study (July 1989 to June 2010). Palepu (1986) posits that earlier studies (such as Simkowitz and Monroe (1971), Belkaoui (1978), Stevens (1973) and Dietrich and Sorensen (1984)) recognise the need to improve the efficiency of models by using non-random equal-share samples which employ an equal number of targets and non-targets[36]. However, these studies fail to control for the inherent sample selection bias by using econometric estimators that implicitly assume random sampling (Palepu (1986)). This, Palepu (1986) argues, '…leads to inconsistent and asymptotically biased estimates of the model parameters and hence biased estimates of the acquisition probability' (p. 7).

Palepu (1986) proposes that the 'rare event' problem can be alleviated by using the state-based sampling methodology alongside appropriately modified estimators such as the conditional maximum likelihood estimator (CMLE) and the weighted maximum likelihood estimator (WMLE). Other researchers (including Manski and McFadden (1981) and Barnes (2000)) have supported the use of state-based sampling when random sampling or the use of equal samples is deemed inefficient. As will be discussed subsequently, most post-Palepu (1986) studies (such as Powell (1997), Barnes (1999), Powell (2004), Brar et al. (2009) and Cahan et al. (2011)) have employed the state-based sampling methodology without recognising its limitations with regards to out-of-sample analysis. This is further discussed in section 2.6.3.

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[36] The alternative is to employ a random sample which, on average, will be made up of 5.28% targets and 94.72% non-targets, in the case of the UK.

ii.) Use of arbitrary cut-off probabilities

Prior research places emphasis on identifying the factors that increase takeover likelihood and/or on developing models that can identify future targets. In the former case, the focus is on the explanatory power of the whole model and the statistical significance of the independent variables in the model. In the latter case, researchers also evaluate the model's ability to predict targets in a holdout sample based on acquisition probabilities. Given that logit models report their predictions in terms of probabilities that are bounded between 0 to 1, researchers (pre-Palepu (1986)) generally used 0.5 as a cut-off probability for identifying prospective targets[37]. Palepu asserts that using a cut-off probability of 0.5 is arbitrary. He contends that the optimal cut-off probability should be dependent on 'the decision context of interest, an appropriate payoff function and the prior state probabilities' (p. 12). Notwithstanding, Palepu's methodology for arriving at an optimal cut-off probability has also been criticised by Barnes (1999) and Powell (2001). The two studies provide alternative methodologies for identifying the optimal cut-off probability for target prediction. This issue is further discussed in section 2.6.4.

iii.) Use of equal-share samples in prediction tests

The relevance of models derived is based on their forecasting ability, i.e., their ability to generate correct 'out-of-sample' predictions of targets and non-targets. This is done by testing the models' predictive ability on a holdout sample. In prior studies which employ 'optimal cut-off probabilities', the key statistic used to measure a model's performance is the prediction error rate[38]. Palepu (1986) notes that predicting a target is like 'searching for a needle in a haystack' – the rare event problem (p. 10). Pre-Palepu studies obscure this difficulty by using a 'contrived sample with a large proportion of targets' in their prediction tests (Palepu (1986), p. 10). The result is that the error rate inferences obtained from such non-random or state-based holdout samples are biased and cannot be generalised to the population. He further argues that there is no econometric justification for employing non-random samples in prediction tests. The unbiased approach is to use a random sample or even the whole population as at a given time, as the prediction sample.

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[37]That is, any firm with a takeover probability of 0.5 and above is considered a target while any firm with a takeover probability below 0.5 is considered a non-target.

[38] The error rate computes the number of targets the model predicts as non-targets (type I error) and the number of non-targets the model classifies as targets (type II error).

Aside from the three proposed methodological corrections discussed above, Palepu (1986) lays a theoretical foundation for the selection of variables for inclusion in prediction models. Early studies such as Simkowitz and Monroe (1971) simply employ a 'kitchen-sink' approach to variable selection augmented by a stepwise procedure to identify unimportant variables for exclusion[39]. Palepu (1986) proposes six acquisition likelihood hypotheses which have been recurrently used in the literature. These include: inefficient management hypothesis, firm undervaluation hypothesis, firm size hypothesis, growth-resource mismatch hypothesis, industry disturbance hypothesis and price-earnings hypothesis. In brief, these hypotheses, respectively, argue that inefficiently managed firms, undervalued firms, small firms, firms which have a mismatch between their growth potential and their resource levels, firms within merger-active industries, and firms with a low P/E ratio are more likely to receive takeover bids. These hypotheses are fully discussed in section 3.3.

In the empirical part of his study, Palepu employs a sample consisting of 163 firms acquired between 1971 and 1979 and a sample of 256 US firms not acquired by 1979. To validate the model, Palepu selects a holdout sample made of 30 targets and 1,087 non-targets[40]. The holdout sample consists of the set of all listed firms (targets and non-targets) in 1980. Using an arguably very low cut-off probability of 0.112 (as noted in Barnes (1999), Powell, (2001) and Powell (2004)), Palepu's model classifies 492 firms as non-targets and 625 firms as targets from the sample of 1,117 firms of which 24 of the predicted targets are actual targets and 601 firms which are not involved in M&A activity are misclassified as targets. The overall accuracy rate is estimated at 45.60% and the concentration of targets in the portfolio is 3.80%. Although the model is statistically significant, its predictive power is very low. As can be expected, investing in the 625 predicted targets over a 250 day holding period generates insignificant cumulative abnormal returns of –1.62%[41]. Palepu concludes that his model does not have a superior predictive ability when compared with the stock market – evidence of market efficiency.

Palepu (1986) presents a systematic and detailed critique of the studies in the first era (1968–1985). Hence, the methodologies applied in these studies are not critiqued further.

[39] Simkowitz and Monroe (1979) started with a set of 24 accounting and market variables and employed step wise regression to reduce this set of variables to seven.

[40] The sample employed in the study is restricted to firms in the mining and manufacturing industry only. This is a likely to limit the generalisability of the results obtained.

[41] Insignificant at the 5% level of significance

As will be discussed, several studies in the second and third era have adopted Palepu's propositions. The starting point of this thesis is the recognition of the limitations of Palepu's propositions (i.e., methodology and hypotheses). Other researchers (such as Ambrose and Megginson (1992), Barnes (1999) and Powell (2001)) have acknowledged some of these weaknesses. Nonetheless, to my knowledge, no study has attempted to address these issues in a comprehensive manner. Besides the Palepu study, other US studies in the second era include: Ambrose and Megginson (1992), Bartley and Boardman (1986, 1990) and Walter (1994).

Ambrose and Megginson (1992), for example, extend the Palepu (1986) study by looking at the effect of asset structure, institutional shareholdings and takeover defences on takeover likelihood. The researchers use a sample of 169 targets and 267 non-targets pulled from the period 1979–1986. The main finding of this study is the fact that US targets are characterised by a high proportion of fixed or tangible assets (tangible assets) within the asset structure. Ambrose and Megginson (1992) explain the result by asserting that tangible assets proxied for operational synergies between targets and bidders, its availability improves the ease of valuation of potential targets, and proxies for asset rich firms in declining industries. Additionally, Ambrose and Megginson (1992) find that the Palepu (1986) model has very little explanatory power when re-estimated using their sample and data. Indeed, none of the Palepu hypotheses are validated using their data (see Ambrose and Megginson (1992), pp. 584–585). Based on this finding, they conclude that little is known about the characteristics of targets. Bartley and Boardman (1986, 1990) and Walter (1994) focus on using prediction models (similar to the Palepu (1986) model) to evaluate the value-relevance of accounting information. These studies have been discussed in section 2.3.5.

2.5.3.3 UK studies

Powell (1997) adopts the hypotheses proposed by Palepu (1986) alongside a multinomial framework for takeover prediction based on his contention that hostile and friendly targets have different characteristics. Powell (1997) employs a UK sample made up of 97 hostile targets, 314 friendly targets and 532 non-targets selected from the period 1984–1991. From his empirical results, Powell (1997) argues that the use of a binomial modelling framework is suboptimal and might lead to incorrect conclusions about the factors driving takeovers. The researcher also finds that the characteristics of targets are time dependent. All the models developed in the study, nonetheless, have a very low explanatory power. Powell

(1997) attributes this poor performance to the reliance on theories (the Palepu hypotheses) which potentially lacked validity or the use of proxies which poorly measured the theoretical constructs.

Barnes (1999) also extends the work of Palepu (1986) by reviewing other relevant statistical and methodological weaknesses of prior research in takeover prediction. First, Barnes (1999) raises the issue of researcher ignorance of the strict statistical assumptions that underlie estimating procedures such as 'multivariate normality' and 'equal-group dispersion matrices across all groups'. Barnes argues that these assumptions are rarely met (as financial ratios are less likely to be normal and more likely to be skewed) and proposes the use of industry-relative ratios[42]. Again, Barnes argues that, to be of use to investors, prediction models need to be stable over time and across industries[43]. Building on Barnes (1999), Barnes (2000) uses a UK sample to test the extent to which targets can be predicted, comparing different models and different variable specifications[44]. Even after including anticipatory share price changes as a new independent variable, Barnes (2000) finds that none of his models (the industry-specific model or the general model) is able to correctly predict any target. In line with this finding, Barnes concludes that his results are consistent with predictions of the semi-strong form of the EMH[45].

Like Powell (1997), Powell (2001) also adopts Palepu's prediction hypotheses, and equal-share samples to estimate the likelihood of a firm being acquired. Powell (2001) extends Powell (1997) by also testing whether abnormal returns can be generated by holding a portfolio of firms predicted as potential targets by the model. The main contribution of this study is to develop a procedure for determining optimal cut-off probabilities which takes into account the investment objective of prediction modelling. The new classification rule, when applied to the holdout samples, results in smaller predicted samples with higher takeover probabilities compared to the Palepu (1986) method (Powell (2001)).

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[42] As will be discussed in section 4.3 the use of logit model as opposed to discriminant analysis circumvents the need to assume multivariate normality.

[43]The difficulty with having a stable model is that a firm's environment changes over time due to changes in inflation, technology, accounting policies, attitudes of acquisition managers, investment officers or merger advisers etc. (Barnes (1990)).

[44] The different specifications included industry-adjusted versus unadjusted variables.

[45] As argued in section 2.4.3, the fact that targets can be predicted does not imply that the market is inefficient. The market is, perhaps, inefficient if investing in predicted targets can consistently generate significant above-market returns for investors.

In the empirical part of the analysis, Powell employs an equal-share UK sample of 471 targets and 471 non-targets to develop his model. The model is tested out-of-sample by using fresh data from 1996. The model predicts that 216 firms will receive a bid in the next period, of which only 7 (or 3.24%) of these firms actually received such a bid. The next stage in the study involves holding a portfolio of all predicted targets over the one year period. Powell (2001) finds that, despite the methodological improvements introduced in the study, the model generated significantly negative abnormal returns during the holding period. Powell (2001) concludes that the results are consistent with the EMH.

2.5.3.4 Summary

Palepu (1986) has remained a seminal paper in this research area, perhaps, for two key reasons; (1) the introduction of theoretically justified takeover prediction hypotheses, and (2) the introduction of an improved methodology for takeover prediction. Some of the studies during this era contribute by further developing new hypotheses (e.g., Ambrose and Megginson (1992) and Powell (1997)) and by critiquing/proposing alternatives to some aspects of the Palepu (1986) methodology (e.g., Barnes (1999) and Powell (2001)). The results from tests on the possibility of generating abnormal returns from prediction models are mostly negative. While Walter (1994) argues that above-average returns can be earned by including current cost information in prediction models, other studies (such as Barnes (2000), Powell (1997) and Powell (2001)), argue (consistent with Palepu (1986)) it is unlikely that using target prediction models can lead to the generation of abnormal returns.

Furthermore, these studies (including Ambrose and Megginson (1992), Barnes (2000), Powell (1997) and Powell (2001)) highlight some of the potential weaknesses in the Palepu (1986) study, particularly his method of computing optimal cut-off probabilities, and the lack of comprehensiveness, sufficiency and validity of his hypotheses and selected proxies. Ambrose and Megginson (1992), for example, do not find evidence to support any of Palepu's hypotheses. The general contention is that little is known about the characteristics of targets. While some of these gaps in research have been highlighted by prior studies, little has been done (in any of the studies during this era) to address issues of theoretical grounding, validity and comprehensiveness of the hypotheses. Further, no study (to the best of my knowledge) highlights the potential limitations of the methods employed by Palepu (1986).

2.5.4 Empirical studies in Takeover prediction 2003–2013

2.5.4.1 Overview

The second era (1986–2002) is marked by a general contention that it is difficult, if not impossible, for takeover prediction to form the basis of a successful investment strategy. The primary reason advanced for this is that target prediction models are inefficient as high levels of prediction errors are recorded. This, perhaps, explains why many studies post-2002, focus on the use of new computational techniques to improve prior takeover prediction models. As will be discussed in this section, several studies in the 2003–2013 era, focus on testing the discriminatory potential of different sophisticated computational techniques rather than actually predicting future takeover targets for investment purposes. Like the studies in the first and second eras, the main studies in this era span different contexts including: the US, the UK and the rest of Europe.

2.5.4.2 US studies

Espahbodi and Espahbodi (2003) is one of the main US studies focusing on the development and testing of takeover prediction models during this era. The study employs both non-parametric (recursive partitioning) and parametric tests (discriminant, logit and probit models) along-side Palepu's (1986) state-based sampling methodology, to develop takeover prediction models for US targets. Aside from using financial variables similar to those in Palepu (1986), Espahbodi and Espahbodi (2003) investigate the relevance of several non-financial variables such as a dummy for anti-takeover regulation[46], a dummy for the presence of poison pills defensive strategies, a dummy for the presence of golden parachutes, and the percentage of directors' ownership within the company. As discussed in section 1.3, the use of these non-financial variables (which broadly capture antitakeover amendments and takeover defences) is particularly important when modelling takeovers in a US institutional setting. These variables are, perhaps, of less importance or even non-applicable (e.g., the Delaware dummy) in the UK setting.

After highlighting the potential relevance of several financial and non-financial prediction variables, Espahbodi and Espahbodi (2003), nonetheless, fail to employ the variables in their analysis as the set of variables are reduced to four main variables (including free cash flow to total assets, golden parachute dummy, Delaware dummy and equity market value to total firm-value) using stepwise regression analysis. Further, Espahbodi and Espahbodi

[46] Firms incorporated in the state of Delaware are subject to more stringent takeover regulations (Espahbodi and Espahbodi, 2003)

(2003) validate their results by testing it on a non-randomly selected sample of 30 targets and 200 selected non-targets. In spite of the biases in the study, Espahbodi and Espahbodi (2003) reported poor predictive ability of all models[47].

2.5.4.3 UK studies

The main UK studies during this era include: Powell (2004), Powell and Yawson (2007), Pasiouras et al. (2007), Ouzounis et al. (2009) and Pasiouras et al. (2010). To a large extent, the focus of Ouzounis et al. (2009), Pasiouras et al. (2007) and Pasiouras et al. (2010) is on the comparison of different parametric and non-parametric modelling approaches using a prediction modelling framework.

Powell (2004) builds on Powell (1997) which proposes a multinomial framework for predicting takeover targets – a framework which differentiates between friendly and hostile targets. Powell (2004) argues that the characteristics of hostile takeover targets are markedly different from those of friendly takeover targets given the fact that the motive for hostile takeovers is to enforce discipline while that of friendly takeovers is to achieve synergies. Powell (2004) contends that a multinomial framework (as opposed to a simple binomial framework) that takes into account the characteristics of the event (hostile or friendly) will produce models with more explanatory power and this will invariably lead to better predictive abilities. Powell (2004) hypothesises that friendly targets are more likely to be small firms in financial distress, having low levels of liquidity and high leverage while hostile targets are more likely to be profitable firms.

Powell employs a UK sample consisting of an estimation sample of 9,891[48] firm-years drawn from 1986 to 1995 and a holdout sample of 1,000[49] firm-years drawn from 1996. The study reports poor model predictive ability as all models (multinomial and binomial) misclassified a large number of non-targets as targets and no model achieves a better than chance predictive ability[50]. Aside from a significant difference in the size of friendly and

[47] Although the recursive partitioning model reported better in-sample classification levels, its superiority can possibly be due to the fact that many more financial and non-financial variables are used in the model while only four variables are used in the discriminant, logit and probit models.

[48] The estimation sample of 9,891 firm-years is made up of 81 hostile targets firm-years, 390 friendly targets firm-years and 9,420 non-targets firm-years.

[49] The holdout sample of 1,000 firm-years is made up of 4 hostile targets firm-years, 25 friendly targets firm-years and 971 non-targets firm-years.

[50] The model is developed using data from 1986 to 1995 and the model is tested using data from 1996. The 1996 test sample of 1,000 firms had 29 targets (a target concentration ratio of 2.9%). Powell (2004) predicted that 268 firms will be targets of which 8 firms are actual targets (a target

hostile targets, the results from the model do not lend support to his contention that friendly and hostile targets have substantial differences. The theorised benefits of a multinomial modelling framework are not, therefore, empirically confirmed in this study. Further, the number of hostile targets in the sample is, perhaps, too few (zero in some years) for a multinomial model to be of any substantial benefit.

Powell and Yawson (2007) focus on factors driving restructuring events. The study investigates whether the variables frequently used in takeover prediction (Palepu's hypotheses plus the tangible assets and free cash flow hypotheses) also explain other restructuring events such as layoffs, bankruptcies and divestitures. Powell and Yawson (2007) employ a sample of 482 takeovers, 82 bankruptcies, 360 divestitures and 631 layoffs between 1992 and 2002. During this period there were no restructuring events in 8,048 firm-year observations. Using a multinomial model, Powell and Yawson (2007) find evidence that takeover targets, firms involved in divestitures and bankrupt firms are all characterised by declining stock returns. The results from the analysis reveals that the variables frequently used in takeover prediction might be more appropriate in modelling divestitures and layoffs than takeovers or bankruptcies[51]. The result of this study further suggests that the set of prediction hypotheses (and variables) used in prior studies does not comprehensively encapsulate the strategic motives of takeovers.

Ouzounis et al. (2009) employ a UK sample of 416 takeover targets and 1,160 non-targets between 2001 and 2005. The study finds that targets are significantly larger in size, potentially undervalued and less profitable when compared to non-targets[52]. The finding on firm size is consistent with Powell and Yawson (2007) but in contrast to prior evidence which suggests that targets are, on average, smaller than non-targets (see, for example, Palepu (1986), Walter (1994), Powell (2001, 2004) and Brar et al. (2009)). The finding that targets have more inefficient management teams and are generally undervalued corroborates earlier research findings (e.g., Palepu (1986), Walter (1994), Powell (2001)

concentration ratio of 2.9%). The implication is that the model developed by Powell (2004) does not predict targets better than a chance or random selection.

51 For example, the results reveal that the likelihood of divestitures is negatively related to a firm's growth, liquidity, stock returns and industry shocks, and positively related to leverage, size, industry growth and industry liquidity, at the 10% level. Similarly, the probability of layoffs is negatively related to growth, size, tangible assets, industry shocks and industry concentration. Nonetheless, the study shows that the probability of takeover is only explained by stock returns, size, industry growth and industry concentration (significant at 10% level), with the relevance of stock returns and size disappearing in some sub periods.

52 The study measured size by using the log of total assets in the previous year. The size variable is significant at a 1% level of significance.

and Brar et al. (2009)). Ouzounis et al. (2009) explore the performance of other non-parametric methods such as UTADIS (Utilités Additives Discriminantes), ANN (Artificial Neural Networks) and SVM (Support Vector Machines). There is no evidence that the more sophisticated non-parametric methodologies consistently outperform a simple discriminant analysis model.

In line with Ouzounis et al. (2009), other UK studies such as Pasiouras et al. (2007) and Pasiouras et al. (2010) have also explored the use of non-parametric models including MHDIS (Multi-group Hierarchical Discrimination Method) and UTADIS (Utilités Additives Discriminantes) in the prediction of UK targets. The objective of these studies is generally to compare the discriminatory ability of these new techniques and not to predict future targets per se. As will be further discussed in section 2.6.2.3, the results obtained to date are mixed with no non-parametric method consistently achieving superior predictive ability over other parametric and non-parametric methods.

2.5.4.4 European (outside the UK) studies

A few studies have considered takeover prediction in a European context. While some researchers have employed a European Union-wide approach (e.g., Brar et al. (2009)), others have focused on a single European country (e.g., Tsagkanos et al. (2007)). In a cross-country European study, Brar et al. (2009) posit that takeover prediction models which incorporate share price momentum and trading volume in their model can be used to generate abnormal returns. Brar et al. (2009) employ the Palepu (1986) hypotheses together with the state-based sampling methodology advocated by Palepu (1986). In terms of target characteristics, the study reports that, '…European targets are smaller in size, undervalued, less liquid, have low sales growth, exhibit strong short-term price momentum and their shares are actively traded prior to the deal announcement' (p. 449). In terms of investment potential, the study ends on a positive note, emphasising that it is possible to generate significant abnormal returns by investing in predicted targets[53]. As will be discussed in section 2.6, the methodology employed in Brar et al. (2009) introduces substantial look-ahead bias into the findings. Primarily, Brar et al. (2009) test their model on the same sample used to develop model parameters.

Tsagkanos et al. (2007) on the other hand, focus on a single EU country by developing a target prediction model for Greece. The study employs a set of variables which presumably

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[53] Brar et al. (2009) report that their model generates 17.4% unadjusted returns (equivalent to 8.5% market-adjusted returns and 10.4% size-adjusted returns), over the holding period.

have unique influences in the Greek economy and a strategic bearing on the decision to acquire Greek firms[54]. The results from the study suggest that Greek acquirers are more interested in large targets, high productivity, accumulated experience and good financial performance. While the study only focuses on a small economy, it highlights the importance of country or context on the choice of prediction variables. It also shows that the relationship between takeover probability and firm variables (e.g., firm size) is likely to be context dependent.

2.5.4.5 Summary

There appears to have been a shift in research focus from developing predictive variables/hypotheses (i.e., understanding the factors that drive takeovers) towards an agenda of testing the ability of different empirical and computational techniques (parametric and non-parametric discriminatory models) to predict future targets. The studies in this era assume (implicitly but not explicitly) that the Palepu (1986) hypotheses fully explain the underlying rationales for takeover. This, perhaps, explains why most of the studies adopt the Palepu (1986) hypotheses but try to improve upon his computational model – the logit model – by employing multinomial models and non-parametric models. The results derived from the different parametric and non-parametric models employed in many of the studies, indicate that these new computational techniques do not, in many cases, improve the accuracy of takeover prediction models[55]. Generally, the models correctly predict very few targets and in so doing misclassify very many non-targets as targets. The effect is that the promised returns to takeover prediction have not been achieved, unless when substantial bias is incorporated in the study[56].

Perhaps, the shift towards the application of 'more advanced' or non-parametric models is pre-mature as a solid foundation for prediction modelling is yet to be laid. For example, evidence from Ambrose and Megginson (1992) and Powell and Yawson (2007) suggest that Palepu's hypotheses do not really explain the strategic rationale for takeovers. A potential way forward is for researchers in the area to revisit the development of predictive hypotheses as knowledge about what motivations/factors drive takeovers is still incomplete. As will be discussed in the next chapter, the current study advances the

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[54]The accounting variables used include; return on equity, net profit margin, leverage, liquidity, debtors' collection period, creditors' payment period, goods' holding period, growth and growth to resource. The non-accounting variables employed include; size, export orientation, relative labour productivity, age and capital to labour.

[55] As will be discussed in section 2.6.2 and 4.3, non-parametric models are not, therefore, adopted in this study.

[56] Such as the Brar et al. (2009) study discussed above.

literature by redeveloping the old hypotheses and introducing new takeover prediction hypotheses prior to the development of prediction models. The result obtained from this study affirms the importance of robust hypotheses development for takeover prediction success.

2.5.5 Takeover prediction by investment practitioners

2.5.5.1 Overview

The goal of this section is to align the research literature with practice and to establish the usefulness and relevance of the methods employed in the area to investment practitioners. Wansley et al. (1983) highlight two early cases of investment firms (E.H Hutton and Dreyfus Company) with investment strategies centred on investing in potential takeover targets. Wansley et al. (1983) notes that E.H Hutton regularly published its 'Acquisition Candidates' brochure devoted to identifying stocks with a high probability of being acquired (p. 149). The Dreyfus Company also managed a Merger and Acquisition Fund with the goal of investing in firms which are likely acquisition targets (Wansley et al. (1983), pp. 149-150). At present, several investors on the internet claim to employ target prediction models as the basis of their investment strategies. Nonetheless, the models employed by these investors are considered to be proprietary and therefore not disclosed. Interestingly, Morgan Stanley IQ and strategists at Deutsche Bank have published the takeover prediction models these firms employ as part of their investment strategies. This published material can therefore provide some useful insights into the practitioners' approach to takeover prediction modelling as an investment strategy. The approaches used by these institutions are discussed below.

2.5.5.2 Target Equity Index Family (2003-2010) – Morgan Stanley IQ

Morgan Stanley runs a Target Equity Index Family (TEIF) as part of its Intelligent Investing programme (Morgan Stanley IQ). This family is a group of five funds made up of a World Target Equity Index, a Europe Target Equity Index, a US Target Equity Index, a UK Target Equity Index and a Japan Target Equity Index. The rationale behind the investing style is embedded in the 'Target Equity' philosophy statement which states: 'Why do some stocks outshine others? While many stocks are perceived as undervalued, not all realise their true value. But sometimes there is a catalyst that brings an undervalued stock to the surface – an event or potential event that may drive a resurgence in the stock price. Some of the largest moves in stock prices can occur when the firms are takeover targets or associated with rumours or potential takeovers. The Target Equity Index Family aims to select undervalued stocks that may be potential takeover targets' (Morgan Stanley IQ (2008), p. 2).

What is intriguing about the prediction of potential targets by Morgan Stanley is the simplicity of the model/methodology employed. The firm indicates that the TEIF, '…uses a screening process that is quantitative, rules-based and transparent. It ranks and selects stocks using inputs from publicly available firm data to create a series of global, regional and country indices' (Morgan Stanley IQ (2008), p. 4).

For potential inclusion in the investible index, Morgan Stanley IQ requires that the stock should be listed on a regulated exchange, must not be in the financial sector and must meet a minimum liquidity criterion[57]. The next step in the selection process employed by Morgan Stanley IQ is to apply its 'Target Equity' screen to the population of firms. This is done by ranking stocks based on five variables: the ratio of free cash flow to enterprise value (FCF/EV), interest cover (EBIT/I), dividend yield (D/P), the ratio of enterprise value to fixed assets (EV/FA) and the ratio of share price to book value (MV/BV)[58]. The final step in the selection process is to pick the 50 stocks with the best ranking across all variables, i.e., stocks with a high FCF/EV, high EBIT/I, high D/P, low EV/FA and low MV/BV. The 50 stocks are used to form an index with equal weighting and the index is rebalanced quarterly (Morgan Stanley IQ (2008)).

Based on self-reported performance in back-tests between April 2001 and July 2007 (Morgan Stanley IQ (2013)), the UK (or world) Target Equity Index generated a total annualised return of 14.40% (or 17.10%) while a broad based index such as the Morgan Stanley Capital Index (MSCI) UK (or world) generated an annualised return of 6.40% (or 0.5%). This leads to an excess return of 8.10% (UK) or 16.60% (world). This period (2001 to 2007) can, perhaps, be viewed as an in-sample period used in the development of the model or the selection of appropriate indication variables. It is therefore expected that the model should perform well during this period. The true test of the model is, perhaps, its performance post-2007.

[57] Sufficient liquidity allows for the formation of a tradable index.

[58] The brochure argues that enterprise value is more suitable when compared to market capitalisation because it captures both the value of equity and the cost of taking over the firm's debt.

Morgan Stanley IQ (2013) reports that the target equity index has not out-performed the MSCI when the methodology is tested 'live' between July 2007 and April 2013. The Morgan Stanley World Target Equity earned an annualised return of –1.5% as against the –0.9% annualised return earned by the MSCI world index. The results show that on a risk-adjusted basis, the model does not generate returns higher than those of the market. In fact, the strategy underperforms the market.

2.5.5.3 Deutsche Bank quantitative strategy – Cahan et al. (2011)

The Cahan et al. (2011)[59] paper is developed by five quantitative strategists working at Deutsche Bank. The paper is published as part of a series of publications on quantitative trading strategies at Deutsche Bank and described as a 'quant approach to takeover prediction' (p. 4). To develop their prediction models, the strategists employ the variables used in Brar et al. (2009) together with informed trading variables, high-frequency trading variables and technical trading variables[60]. These variables attempt to capture the sentiments of other market participants (such as option traders, technical traders and high-frequency traders) by examining the minute-to-minute movements in stock prices.

The Weibull Shape Parameter, for example, measures the time between trades on a particular stock. If the time between trades suddenly drops (i.e., higher frequency trading), then it is probable that informed traders are predicting an event (such as a bid) to occur. Similarly, the Residual PIN uses data from individual trades (tick by tick data) to infer the likelihood of informed trading or information leakage (i.e., the likelihood that traders are expecting an event to occur). The rationale for using these different variables is fully discussed in Cahan et al. (2011).

By employing a logit regression model on the sample of Russell 3000 stocks, the strategists find that targets have a higher price to earnings, lower price to book, higher gearing, good gross margins, are within active M&A sectors, have lower trading volume, lower market capitalisation, higher total assets, lower price volatility, fat tails in daily returns, higher option trading volume and positive intraday return skewness. Some of the

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59 At the time of writing (2011), the lead researcher, Rochester Cahan, is the Director at Deutsche Bank, heading the US quantitative strategy team.

60 Informed trading variables include the ratio of dollar value of options traded to stocks traded (O/S ratio), Weibull Shape parameter, Intraday Order Imbalance, Residual PIN, and Intraday abnormal turnover. High-frequency trading variables include; high-frequency standard deviation, high-frequency skewness, and high-frequency kurtosis. Technical trading variables include; daily volatility, daily skewness, daily kurtosis, and abnormal volume. The data for some of these variables (e.g., high-frequency trading) is only available in a limited number of years.

results presented by Cahan et al. (2011) are counter intuitive or even contradictory. For example, the finding that targets have small market capitalisation and large total assets is, possibly, contradictory as total asset and market capitalisation are both used as proxies for firm size[61]. Perhaps, this is because some of the variables included in the model (e.g., price to earnings and price to book, market capitalisation and total assets, and stock trading volume and options trading volume) are likely to be highly correlated. Cahan et al. (2011), on average, achieve a target concentration of just 0.8% using their high-frequency model which predicts targets on a monthly basis[62]. When its abnormal returns are considered, the model substantially underperforms the market in all periods between June 2001 and June 2011.

Cahan et al. (2011) contend that the poor results are attributed to a 'loser drag' as 'false positives' are on average 'loser stocks' and the benefits from a few predicted targets do not outweigh the cost of holding these 'loser stocks' (p. 18). The strategists argue that underperformance within the target portfolio can be mitigated by applying an in-house proprietary screening procedure (Deutsche Bank QCD model) on all predicted targets to further screen the list of predicted targets for loser stocks. The results show that the high-frequency model employed in this study neither has a superior predictive ability nor provides a superior investment tool.

2.5.5.4 Summary

This section highlights the relevance of target prediction modelling to the investment community by drawing examples from two key investment banks – Morgan Stanley and Deutsche Bank. There is a substantial difference in the approach employed by the two institutions, with Morgan Stanley employing a simple 'rank-based' model (which ranks firms across five variables) and Deutsche Bank employing a sophisticated high-frequency 'quant-based' model. While Morgan Stanley describes its model as one which 'aims to select undervalued stocks that may be potential takeover targets' (Morgan Stanley (2008), p. 2), there is no empirical evidence that the model can actually predict any actual targets. Cahan et al. (2011) present empirical evidence which shows that their model only slightly

[61] The study also employed the non-random equal-share or matched sampling procedure used in studies such as Brar et al. (2009) and Palepu (1986).

[62] The strategists employ deciles rather than any cut-off probability. The use of deciles on the Russell 3000 leads to a prediction that 300 stocks should receive bids each month. Of these 300, only 2.4 stocks (0.8%) on average received a bid each month.

improves on a strategy of holding all the stocks in the Russell 3000 index[63]. Overall, the results suggest that the two practitioner models neither have a superior predictive ability nor a superior ability of generating above normal returns for investors.

2.5.6 Takeover probability as an input variable in empirical research

As discussed in section 2.3.6, a range of studies including Cremers et al. (2009), Bhanot et al. (2010) and Cornett et al. (2011), amongst others, have employed takeover probabilities as a key input variable to investigate different research questions. Cremers et al. (2009), for example, develop a model to predict takeover targets, with the objective of testing the impact of takeover likelihood on firm valuation. They employ a US sample of firms between 1981 and 2004. In the study, the takeover likelihood is defined as a probit function of a firm's Q ratio, tangible assets, cash resources, blockholders' dummy, size, industry leverage and return on assets. Cremers et al. (2009) report that between 1991 and 2004, the prediction model generates annualised mean abnormal returns of 7.95%. Nonetheless, these returns are not explained by the targets in the sample as the returns persist (at a similar magnitude) when actual targets are excluded from the sample. The study concludes that a takeover factor (derived from firm takeover likelihood) partly explains the cross section of firm returns and the returns to governance-based (G-index; Gompers et al. (2003)) portfolios.

Bhanot et al. (2010) investigate the effect of a firm's takeover risk on the relationship between its stock returns and bond prices. Takeover risk in this study is defined as a function of firm size, market to book ratio, excess returns, EBITDA, R&D, level of tangible property, leverage, percentage of institutional ownership and one-year price volatility. Only completed takeovers are considered and a probit regression model is used to obtain the takeover probability. No validation tests are conducted to ascertain the validity of the model in computing firm takeover probability.

Further, Cornett et al. (2011) investigate investors' anticipation of bidder and target candidacy in takeovers and whether this anticipation moderates the wealth distribution between bidders and targets in takeovers. In the research design, bid probability or risk of takeover for targets (probability of making a bid for bidders) is used to develop a surprise instrument (a measure of market anticipation). Cornett et al. (2011) model bid probability

[63] Cahan et al. (2011) indicate that about 180 Russell 3000 stocks receive a bid each year (15 bids each month). Their model is able to predict an average of 2.4 targets each month (from a pool of 300 firms) or 24 targets each year (from a pool of 3000 stocks).

as a logit function of sales shock, size, change in size, industry concentration, growth-resource mismatch, return on assets, cash ratio, price run-up, information asymmetry and participation in previous mergers. Like in the previous two studies, the validity of the model in measuring the likelihood of being a bidder or target is not further tested in the study.

The validity of these three studies (Cremers et al. (2009), Bhanot et al. (2010) and Cornett et al. (2011)) is, perhaps, reliant on the models efficiency in measuring takeover risk. These three studies do not, however, test whether the models can predict future targets. Further, the variables used in the definition of takeover risk in these three studies are a mix of the variables that have recurrently been used and criticised (for lacking explanatory power) in prior empirical research. Perhaps, the true test of a prediction model or one that measures takeover risk is not whether it generates abnormal returns (like in Cremers et al. (2009)) but whether it is able to predict the event in question (future targets or bidders). It is unclear whether a more optimal takeover risk model will alter the conclusions of these studies.

2.5.7 Conclusion

The review has shown that takeover prediction and takeover probability modelling is truly a broad field with a strong historical background. The review has also shown that the literature has resorted to the propositions made by Palepu (1986) with marginal improvements in modelling techniques. Takeover prediction is of interest to investors, with investor models seeming to mirror the models used in academic empirical research. As discussed in section 2.5.6, several contemporary studies are employing takeover probability (however defined) as an input in different areas of empirical research. These studies do not, however, evaluate the empirical validity of the takeover likelihood models developed. The next section (2.6) critiques the methodologies that have been used in post-Palepu (1986) studies. The aim is to put in place a more robust methodological framework for developing and testing takeover prediction models. A key part of this framework is the development of a new set of predictive hypotheses derived from theory. The development of these hypotheses is the subject of chapter 3.

2.6 An evaluation of methodological choices of prior studies

2.6.1 Overview

The Palepu (1986) study provides a comprehensive critique of the studies in the pre-Palepu era which are discussed in section 2.5.2. This critique is summarised in section 2.5.3.2. The focus of this section is to critically evaluate the methodology recommended by Palepu (and adopted by several of the studies discussed in section 2.5.3 and 2.5.4), as well as some of the empirical methods, choices and techniques used in more contemporary studies. Different aspects of the prediction methodology (including: (1) the choice of discriminatory models, (2) sampling strategies, (3) the choice of cut-offs for identifying targets out-of-sample, and (4) the choice of prediction hypotheses) are evaluated.

2.6.2 Choice of discriminatory models

2.6.2.1 Overview

Several discriminatory models have been used by researchers in the various attempts to predict takeover targets. The methods employed include: univariate analysis such as difference of means testing, linear discriminant models, logistic regression models, neural network models, recursive partitioning models, multinomial logit models, support vector machines, rough set models, quadratic discriminant analysis, multi-criteria decision aids and probit regressions, amongst others (see, for example, Palepu (1986), Powell (2001, 2004), Barnes (2000), Espahbodi and Espahbodi (2003), Pasiouras et al. (2007), Brar et al. (2009), Ouzounis et al. (2009), Bhanot et al. (2010)). A summary is presented in table 2.6.2. For the purposes of this study, these techniques are broadly classified into parametric and non-parametric techniques.

2.6.2.2 Parametric techniques

Parametric analysis generally assumes knowledge of the nature or functional form of the distribution from which data is drawn. Most popular statistical models (some of which are discussed below) are parametric in nature. Knowledge of the nature of the distribution allows inferences about the model parameters to be made. Regression analysis (linear, logistic and probit) is a key parametric technique which has been widely used in prediction modelling. Prior researchers such as Steven (1973), Wansley et al. (1983) and Rege (1984) employed linear discriminant analysis (LDA) to predict future targets. The popularity of this model amongst early researchers can, perhaps, be attributed to the success of the early bankruptcy prediction models such as Beaver (1966), Altman (1968) and Taffler (1983) which also employed linear discriminant models. Some more recent studies such as Espahbodi and Espahbodi (2003) have also applied linear discriminant models[64].

Researchers such as Zavgren (1983), Palepu (1986) and Balcaen and Ooghe (2006) have criticised the use of LDA in takeover and bankruptcy prediction, noting that the model is based on assumptions which are highly violated in prior research. For example, LDA assumes that the independent variables follow a multivariate Gaussian distribution. Palepu (1986) and Balcaen and Ooghe (2006) contend that this particular assumption is very often violated. Barnes (1990) contends that financial variables are less likely to be normally distributed and more likely to be skewed. The consequence of using such financial variables in the model is that standard errors and significance tests become unreliable. The requirement for multivariate normality also limits the use of qualitative predictor variables (such as dummy variables) in LDA. Hence, controlling for industry effects, for example, through the use of industry dummies, becomes inappropriate.

When distinguishing between targets and non-targets, the LDA assumes that the target and non-target subgroups have equal variance-covariance matrices. This implies that dispersion matrices for targets and non-targets should be the same, which is often not the case. Balcaen and Ooghe (2006) argue that in instances where this assumption cannot be met, quadratic LDA (though more complex) will provide a more appropriate solution. The third assumption of linear discriminant modelling requires that, prior probabilities of group membership are known together with misclassification costs (costs of type I and type II errors). The likelihood that firms will be subjects of takeovers is contingent on several factors which may include environmental factors which are unstable over time. It is therefore difficult to determine *a priori* with certainty, the probability of group membership and hence the misclassification cost.

Finally, the LDA model requires that independent variables should be free from multicollinearity. Multicollinearity leads to unstable parameter estimates (Brookes (2008)) and therefore inaccurate models with low predictive abilities. Multicollinearity occurs when the independent variables are interrelated or correlated i.e., when one independent variable is a function of another. The main effect of multicollinearity is that it leads to broader confidence intervals and smaller t-statistics (see Brookes (2008) and Gujarati

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64 Linear discriminant models (LDA) employ linear regression analysis to obtain a score which is a function of several firm characteristics. The model stipulates that the probability that a firm will receive a bid is a linear function of a vector of firm variables.

(2007) for a fuller discussion on the source and consequences of multicollinearity). Critics of bankruptcy and takeover prediction studies (e.g., Palepu (1986), Balcaen and Ooghe (2006)) note that few researchers using discriminant analysis test if their data actually meet the assumptions of the models. The consequence is that some of these models are potentially mis-specified, and are likely to lack explanatory and predictive ability.

The logit model has been proposed and employed in takeover prediction as it circumvents some of the problems inherent in LDA. The model stipulates that the probability that a firm will receive a takeover bid is a logit function of a set of firm characteristics. Several researchers (including Barnes (1999)) argue that logit models are theoretically and empirically superior to LDA in the context of takeover prediction. The suitability of logit models over LDA is based on its less restrictive assumptions. Logit models do not assume a linear relationship between independent and dependent variables. This implies that logit models can handle nonlinear effects (such as U-shaped relationships), without mis-specifying the model parameters. Again, the dependent variables that go into a logit model need not necessarily be interval scaled, unbounded or normally distributed. This implies that dummy variables can be used as proxies and explicit interaction, as well as power terms can be added to a model without mis-specifying the model's parameters. Unlike LDA where the output is unbounded, the output from logit regression is bounded between 0 and 1 (corresponding to a probability scale), allowing for meaningful and direct interpretation. The assumptions of logit models are fully discussed in Allison (2012).

The rare event problem poses a threat to the validity of using logit regression models in takeover likelihood modelling. King and Zeng (2001) contend that logit regression models can sharply underestimate the likelihood of rare events. They suggest that the effects of this rare event problem can be eliminated by using a large sample. Some researchers such as Bhanot et al. (2010) have employed probit models (as opposed to logit models) as the base model for takeover likelihood modelling. The key difference between these models is their assumption of the shape of the underlying probability distribution (further discussed in Brookes (2008)). Brookes (2008) contends that in large sample analysis, where the split of the dependent variable between 0 and 1 is balanced, the difference between the probit model and the logit model is insignificant. The case of takeovers represents an unbalanced case as the number of targets is usually significantly less than 10% of the total population (further discussed in section 4.2). Using a large sample, nonetheless, minimises any bias originating from choice of model as the difference in the results obtained from either link (logit or probit) functions approaches zero as the sample size increases (Greene (2003)). Table 2.6.2 shows the parametric and non-parametric techniques that have been employed across the takeover prediction literature to date.

Table 2.6.2: Modelling techniques employed in prior research

Study	Period	Country	Model(s)
Belkaoui (1987)	1960-1968	Canada	Linear Model
Rege (1984)	1962-1973	Canada	Linear Model
Brar et al. (2009)	1992-2008	EU	Logit Model
Pasiouras et al. (2006)	1998-2002	EU	Multi-Criteria Decision Analysis
Zanakis and Zopounidis (1997)	1983-1990	Greece	Linear Model
Tsagkanos et al. (2007)	1995-2001	Greece	Logit Model
Slowinski et al. (1997)	1983-1990	Greece	RSM
Tzoannos and Samuels (1972)	1967-1968	UK	Linear Model
Barnes (1990)	1986-1987	UK	Linear Model
Ouzounis et al. (2009)	2001-2005	UK	Linear Model, ANN, UTADIS, SVM,
Barnes (1998)	1991-1993	UK	Logit Model
Barnes (1999)	1991-1993	UK	Logit Model
Powell (1997)	1984-1991	UK	Logit Model
Powell (2001)	1986-1995	UK	Logit Model
Powell (2004)	1986-1985	UK	Logit Model, Multinomial Logit Model
Tartari et al. (2003)	1998-2000	UK	SG, Linear Model, UTADIS, PNN, RSM
Doumpos et al. (2004)	2000-2002	UK	UTADIS
Espahbodi and Espahbodi (2003)	1993-1997	USA	Logit Model, Linear Model, RP, Probit Model, QDA
Wansley et al. (1983)	1975-1976	USA	Linear Model
Bartley and Boardman (1986)	1978	USA	Linear Model
Bartley and Boardman (1990)	1975-1981	USA	Linear Model
Simkowitz and Monroe (1971)	1986	USA	Linear Model
Stevens (1973)	1966	USA	Linear Model
Wansley and Lane (1983)	1975-1977	USA	Linear Model
Ambrose and Megginson (1992)	1981-1986	USA	Logit Model
Cornett et al. (2010)	1979-2004	USA	Logit Model
Cremers et al. (2009)	1981-2004	USA	Logit Model
Dietrich and Sorensen (1984)	1969-1973	USA	Logit Model
Palepu (1986)	1971-1979	USA	Logit Model
Walter (1994)	1981-1984	USA	Logit Model
De and Jindra (2012)	1980-2006	USA	Multinomial Logit Model
Bhanot et al. (2010)	1980-2000	USA	Probit Model

Notes: The table summarises sample period, sample country and modelling techniques used across different prior studies in takeover prediction. The table is ordered by sample country. The techniques used are as follows: UTADIS (UTilites Additives DIScriminante), PNN (Probabilistic Neural Network), ANN (Artificial Neural Networks), RP (Recursive Partitioning), QDA (Quadratic Discriminant Analysis), SVM (Support Vector Machine), RSM (Rough Sets Model). The most conventional techniques employed are the logit and linear models.

The table shows that the logit model is the model of choice for many researchers. While the use of linear models (linear regression analysis or multiple discriminant analysis) was quite popular pre-1986, their use in modelling takeover likelihood has declined substantially over time. The table also reveals that the last decade has seen the introduction of several other 'non-parametric' models into the prediction literature. This is further discussed in the next section.

2.6.2.3 Non-parametric techniques

As shown in table 2.6.2, several non-parametric (and semi-parametric) predictive modelling techniques have been introduced over the last decade. The recent upsurge in the use of non-parametric techniques has been in line with recent developments in computational technology. Examples of these models include recursive partitioning, neural networks, support vector machines, rough set models and decision trees, amongst others.

Unlike parametric models, non-parametric models do not generally assume *a priori* knowledge of the underlying distribution from which data is drawn. The attractiveness of these models stems from the fact that the researcher does not need to hypothesise on the underlying relationship between the dependent and independent variables prior to modelling. Pasiouras et al. (2007) note that non-parametric models are advantageous when compared to parametric models since they do not require any assumptions to be made (such as the need for multivariate normality) and therefore allow for the incorporation of non-quantitative variables into the model. It is worth reiterating that logit models also have less restrictive assumptions similar to those of non-parametric models. As evidenced by prior research (Pasiouras et al. (2007), Ouzounis et al. (2009)), non-parametric models are likely to be better fitted to the training data[65] given their flexibility in accommodating nonlinear patterns and other data dynamics. Nonetheless, they are less likely to have a superior predictive ability when applied to a holdout sample, as the models are sample-specific. A major limitation of these models (for empirical research) is their inability to explain the underlying relationships between the dependent and independent variables.

Espahbodi and Espahbodi (2003) directly compared the performance of parametric and non-parametric models in takeover prediction. Their results show that recursive partitioning has a higher in-sample classification ability compared to the parametric methods used in the study, but underperformed out-of-sample. They further contend that,

65 Training samples constitute the data employed in the development of the model. This is discussed further in section 2.6.4.2

unlike the parametric methods, recursive partitioning does not allow for firms to be ranked or compared based on their takeover probability. That is, the algorithm simply classifies firms as 'targets' or 'non-targets' without information on the degree of semblance to targets and non-targets. Espahbodi and Espahbodi (2003) also argue that non-parametric models are bound to perform poorly out-of-sample as the models are specific to the variables, sequence of variables used and other user-specific choices such as splitting values and number of splits.

Other researchers (such as Pasiouras et al. (2007), Zopounidis and Doumpos (2002) and Doumpos et al. (2004)) have employed non-parametric models such as MHDIS, SVM and UTADIS. Pasiouras et al. (2007) show that, when compared against each other, these models have different merits, with MHDIS having the highest out-of-sample predictive ability and UTADIS having the least out-of-sample predictive ability[66]. The issue of interest in this area of research is whether the more sophisticated models perform significantly better than the traditional models. Several researchers argue against the purported benefits of these 'more sophisticated' models. Summarising the evidence across different research areas, Balcaen and Ooghe (2006) conclude that the benefits to be gained from using more sophisticated models are questionable as much of the evidence shows that they don't perform substantially better than the standard parametric models.

2.6.2.4 Summary

This section has looked at the different models (parametric and non-parametric) applied across research in takeover prediction. It has been shown that linear discriminant models are limited due to several assumptions which govern their use. Many researchers have substituted linear discriminant models for logit models due to its less restrictive assumptions and the ease of interpreting its results. As discussed in section 2.6.2.3, non-parametric techniques are similar to 'black box' models which do not allow for the interaction between the independent variables and their relationship with the dependent variable to be understood. Non-parametric techniques are, therefore, less likely to be useful to stakeholders interested in understanding the dynamics of the takeover process.

[66] No tests are however done to show that the difference in performance across models is statistically significant.

2.6.3 Strategies employed in Sample construction

2.6.4.1 Overview

Sampling has remained a challenge in takeover prediction modelling due to the rare event problem. As will be shown in section 5.2, just over 5.28% of UK firms, on average, receive a takeover bid each year (between 1989 and 2010). Given the problems that such a data distribution can generate in regression analysis (discussed by King and Zeng (2001)), many researchers resort to use contrived (rather than random) sampling methods in model development and/or out-of-sample model testing. The problem (i.e., using contrived or non-random samples) is exacerbated when researchers rely on statistical tests that assume random sampling (Palepu (1986)). This sampling limitation and other biases arising from the way in which training and holdout samples are selected are discussed in this section.

2.6.4.2 Training samples: matched-samples versus panel data approach

Training or estimation samples constitute the data employed in the development of the model and the computation of its parameters. Prior research argues that reliance on random sampling methods in the construction of training samples is simply inefficient as the number of non-targets significantly dwarfs the number of targets. Palepu (1986), for example, argues that the use of a purely random sample (with a small proportion of targets) will result in the obtainment of a sample with low information content and lead to 'imprecise parameter estimates' (p. 6). Building on Palepu (1986), researchers such as Hasbrouck (1985), Bartley and Boardman (1990), Barnes (1990, 1998, 1999, 2000), Powell (1997, 2001) and Brar et al. (2009), amongst others, have employed state-based samples (or a matched-sampling approach) in order to circumvent the rare event problem.

Palepu (1986) describes his sampling approach as follows. 'A total of 277 targets are initially identified. Of these, 163 are included in the estimation sample after screening for data requirements. The population of 2,054 firms, which are not acquired as of 1979 and satisfied the criteria for inclusion in the sample as non-targets, is first arranged in alphabetical order. Every sixth firm is selected from this list to generate a random group of 343 non-targets. Of these, 256 firms met the data requirements and are included in the sample' (p. 20). Palepu (1986) employs a match-sampling technique that results in a reduction of the number of non-targets in his sample from 2,054 to 256. This allows him to increase the proportion of targets to non-targets from 7.3% to 38.9%. This contrived sample, perhaps, significantly obscures the difficulty of finding a target in the sample.

A similar procedure is used in Brar et al. (2009), who describe the procedure as follows. ‘For every year in our study we generate a random sample of firms from the non-target population. We call this sample a ‘control’ group. The size of each control group matches the percentage of M&A activity in the reference year to the total activity over the entire period. If for example, 10% of M&A activity takes place in 1998, we randomly assign 10% of the non-target firms to 1998’ (p. 435). Brar et al. (2009) have a sample of 894 European targets (successful and unsuccessful bids between 1991 and 2003) and 2,906 European non-targets (firms that did not receive a bid in any year between 1991 and 2003). Brar et al. (2009) choose not to adopt a panel data framework (which would have increased the number of non-targets to 34,872 non-target firm-years) but to adopt a matching procedure that matches non-target ‘firms’ to target ‘firm-years’.

While the selective sampling methodology for non-target selection described above is problematic in itself (as will be discussed below), a major concern (and potential source of bias) is the non-systematic way in which specific non-target cases are selected for inclusion in the sample across different studies. The approach used, generally referred to as the ‘matching criterion’, is quite varied across prior research. Prior researchers have adopted various matching criteria including matching by size, matching by year-end, matching by industry, and random matching, amongst others. Bartley and Boardman (1986, 1990) argue that any form of matching is arbitrary due to the lack of a theoretical explanation to justify the matching criterion but suggest that when the ‘objective is simply to examine the statistical significance of predictive variables’ then matching by size, industry and time might be sufficient (Bartley and Boardman (1990), p. 55). While state-based sampling, potentially, gives an indication of the relevance of prediction variables (as suggested by Bartley and Boardman (1990)), it also, perhaps, leads to misspecification of model coefficients (and particularly the magnitude of coefficients). Coefficients do not capture the true difficulty of identifying a ‘needle in a haystack’[67] and therefore leads to high out-of-sample misclassification when the model is used in prediction.

State-based sampling methods, typically, consider only live firms (see, for example, Palepu (1986), Ambrose and Megginson (1992), Barnes (1998, 1999, 2000), Powell (1997, 2001) and Brar et al. (2009)). The procedure recommended by Palepu (1986) and employed in the above studies is to identify all targets over the study period and to match these targets

[67] Palepu (1986) describes the difficulty of finding a target in the population of firms as finding a ‘needle in a haystack’.

to the set of non-targets (i.e., surviving firms) at the end of the study period. By considering only surviving firms, the sampling process employed by several researchers (such as Palepu (1986) and Brar et al. (2009), amongst others) incorporates substantial survivorship bias. The implication is that, the models developed are not trained to distinguish between potential targets and potential dead (bankrupt, liquidated, receivership) firms, which is an important consideration from an investment perspective. This survivorship bias can, perhaps, partly explain why the models developed in previous research have reported significant error rates in out-of-sample prediction. For models to be useful in out-of-sample (equivalent to 'real-world') prediction, their coefficients need to be developed using representative training samples. This is further discussed in chapter 4.

Overall, the use of a state-based sampling methodology for model development cannot be justified from a 'prediction for investment' perspective. The state-based sampling method undermines the reality that M&A is a rare and difficult-to-predict event. The parameters of models developed using state-base samples do not capture the true nature of the data. Such models are likely to lack any generalisability or out-of-sample explanatory power[68].

2.6.4.3 Holdout samples

Prediction models are developed using a training sample but need to be validated out-of-sample. If validation is done using the training sample, the predictive accuracies are likely to be biased upwards. For a holdout sample to be relevant for prediction testing, it is important for such a sample to reflect the challenges faced in real life usage of the model. Brar et al. (2009) can be criticised on this basis as they employ the same period to develop and to validate their model[69].

The method of using a holdout sample to test predictive ability of a model proposed by Palepu (1986) and widely used in the takeover and bankruptcy prediction literature (see studies by Powell (2001, 2004), Barnes (1999, 2000)), leads to results that are, potentially, negatively biased. Palepu (1986) correctly argues that, out-of-sample tests are required to

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[68] In section 6.5, for example, I discuss two studies by Powell (2001 and 2004) which apply the same data set and variables but different sampling methods. The results from this comparison suggest that a state-based sampling methodology underperforms a random-sampling method in out-of-sample analysis.

[69] Brar et al. (2009) use data from 1992 to 2003 to develop their model, then fit the model on data from 1995 to 2003 (p. 447). Several biases are apparent. First, their sample has very few targets (16 targets) between 1992 and 1994 (see table 1, p. 443, Brar et al. (2009)). This potentially explains why 1995 (with 31 targets) is used as a start year to fit the model. Second, while they argue that their model is tested out-of-sample, no apparent tests or results are presented. It is unlikely that any such tests are conducted as the model is fitted using data from 1995.

investigate the predictive ability of models. Palepu (1986) uses a static sample of firms from 1970–1979 to construct his model and a sample of firms from 1980 to test the predictive power of the model. The sample is described as 'static' as no consideration is given to the exact year (time) from which the data is drawn. The use of static-type models is not consistent with the cause-and-effect assumption underlying the modelling process – firm characteristics (e.g., management inefficiency) lead to takeovers. For example, when matched samples are employed, no attempt is made to capture 'causation' by using time-lagged data to explain the event. For each firm in Palepu's prediction sample, his model is validated only if a firm is a target between January 1980 and December 1980. Firms subject to a takeover in January 1981, for example, are not considered as targets. The implication is that the holdout sample test might show that the model performs poorly even if several of the predicted targets are acquired in January 1981. This introduces a time dependency in hold-sample tests which is not captured during the model development process[70]. This time-dependency in prediction tests, potentially, leads to negatively biased model performance results.

As will be discussed further, this problem cannot simply be alleviated by extending the test window beyond a 12-month period (as there is no theoretical or empirical justification for applying any test window in the context of static-type models). Static-type models only help to classify firms into different groups on the basis of their similarity to either targets or non-targets. These models are unlikely to offer any guidance on the time line within which firms with semblance to target firms should receive a takeover bid. Several studies adopting the Palepu (1986) methodology fail to recognise this time independency and therefore have introduced bias to their model tests. This issue can, perhaps, be resolved by developing more dynamic models using time varying covariates, incorporating appropriate lags and adding timing factors into prediction models.

Timing and causation can, perhaps, be factored-in implicitly through the use of more dynamic models which employ time-varying covariates and a suitable lagging framework (i.e., a framework that supports the cause-and-effect assumption). In bankruptcy prediction research, Shumway (2001), for example, proposes a hazard-type model employing up to three years of historical data for each target in the sample. This hazard-type model is more

[70] That is, the out-of-sample test is evaluating the model's ability to predict firms that will be the subject of a bid between specific dates (January 1980 and December 1980) while the model was developed using a static framework with no regard for time or year in which a bid was made in the estimation sample.

efficiently able to model the 'time to death' (Shumway (2001)) or the probability that a firm will receive a bid during its next financial year. In addition, timing can also be incorporated explicitly, perhaps, through the incorporation of 'timing factors' (such as market variables), which serve to provide additional clues as to how soon a firm can be expected to receive a bid. These factors are likely to improve timing by incorporating both market and economic environmental factors which may act as a catalyst or an inhibitor to takeover activity.

The use of a 12-month out-of-sample test period can be empirically justified when time-varying covariates are employed in the model. Equation 1.2.3(1) is restated as below, where the likelihood of a firm (i) becoming a target (or receiving a takeover bid) in a period (T), denoted by $Prob_{iT}$, is modelled as a function of a vector of its characteristics(α_i) in the most recent period (T–1) in which these characteristics are observable, denoted by $f(\alpha_{iT-1})$.

$$Prob_{iT} = f(\alpha_{iT-1}) \dots \dots \dots Eqn\ 1.3.3(1)$$

This framework allows for T to be more clearly empirically specified. For example, a T of 12 months will allow for the computation of the probability that firm (i) will become a target in the next 12 months based on its observable characteristics in the last 12 months. The coefficients of the model will be trained to recognise this time dependability and hence will be optimal in out of sample prediction.

2.6.4.4 Time lapse between firm year-end and date of data availability

Fama and French (1993) raise the issue of a time lag between firm financial year-end and the actual date of data publication. Many US and UK firms have a financial year-end of December which coincides with the Calendar year-end (see Fama and French (1993) for US evidence and Soares and Stark (2009) for UK evidence). Fama and French (1993) apply a lapse of six months by assuming that June X2 represents a realistic date by which firm financial data for year-ending December X1 is publicly available. Building on Fama and French (1993), Soares and Stark (2009) note that a significant proportion of UK firms have a December year-end and the regulation allows public firms to publish their financial results within six months of their financial year-end. In fact, prior to 6th April 2008, the UK Companies Act allowed firms to file in their reports up to seven months after year-end. This is further discussed in section 4.2.5.

Prior target prediction studies do not account for the likelihood that firm financial data will only be publicly available several months after firm year-end. This, perhaps, leads to look-ahead bias in prediction tests as takeover probabilities are computed using data which is not in the public domain. In section 4.2.5, the 'June approach' (discussed in Soares and Stark (2009)) is adopted and used to mitigate such look-ahead bias.

2.6.4.5 Coverage of training and holdout samples

There is no clear empirical guidance on how much data (how many years of observations) should be used to develop or test prediction models. Barnes (2000) contends that the significance of prediction models and hypothesis changes over time. In line with this, Powell (1997) argues that takeover likelihood models are not robust over time due to frequent changes in the macroeconomic environment that impose changes in the firm's operating conditions. Powell (1997) advocates the use of training samples covering short time periods as a way of circumventing the lack of robustness inherent in long time periods. In support of this, Espahbodi and Espahbodi (2003), for example, construct their sample by employing US data from 133 takeover bids announced in the last six months (July to December) of 1997[71].

Traditionally, the preference has been to employ time periods which maximise data usage. The use of longer periods of analysis can allow the researcher to document important changes in the relevance of takeover prediction hypotheses and theories over time. It is shown in this study that the length of the time period used in model development impacts on the model performance (further discussed in chapter 6). Given that there are no theoretical prescriptions on how samples should be constructed, the potential bias arising from the choice of sample time period can, perhaps, be mitigated by showing that results are consistent when different alternatives are employed.

Several researchers (including Palepu (1986), Walter (1994) and Powell (2001, 2004)) have tested the potential for prediction models to generate abnormal returns for investors by computing the abnormal returns generated by the models over a period of one year.

[71] On the contrary, Brar et al. (2009) employ a 12-year time span from 1992 to 2003, obtaining a sample of 896 bid announcements. They note that more than 50% of the bids considered in their sample are made between 1999 and 2000, with UK targets making up over 40% of the sample. The implication is that the likelihood of firms receiving a bid in their static sample is time dependent, with firms more likely to receive a bid between 1999 and 2000 than during the rest of the period. As discussed in 2.6.4.3, this problem of lack of robustness over time (and hence the preference for short time period sampling) can, perhaps, be mitigated through the use of dynamic models, incorporating timing factors as well as time varying covariates.

Powell (2004), for example, tests his multinomial model by holding a portfolio of predicted targets through the period from January 1996 to December 1996. From the model's performance during this one-year period, he contends that his multinomial model is better than the binomial model and can lead to the generation of abnormal returns.

From an investment standpoint, it is necessary to test a model's ability to generate abnormal return over several years. This will allow the modeller to ascertain if the model performs consistently enough to be a useful investment tool. In line with the discussions on the EMH in section 2.4.3, a valid test of EMH is not whether the model can generate abnormal returns in one single year (which could be an outlier), but whether it can do so consistently over several time periods. A misleading picture of the model's potential to generate positive returns can be painted, if, for example, that single year corresponds to a year when the entire stock market experienced high growth levels (such as 1996, employed in Powell (2001, 2004)). A more robust performance test can evaluate how the model performs under different market conditions, across different years and whether the model's long run average performance (when adjusted for the level of risk) is different from that of the entire market. Such an approach is adopted in the current study as will be further discussed in chapter 4.

2.6.4.6 Summary

This section highlights some weaknesses and biases in the sampling methodology employed in prior studies. These include the use of matched-samples in estimating model parameters, the evaluation of model performance on inappropriately designed holdout samples, the failure to recognise the time lapse between firm year-end and financial data availability and the coverage of training and holdout samples. The exact impact of these biases on the conclusions of different prior studies is difficult to discern. These study advances the literature by proposing and adopting a more robust sampling framework (discussed in chapter 4). This framework is applied to re-evaluate some of the conclusions of prior studies.

2.6.4 Cut-offs and other methods for selecting the optimal target portfolio

2.6.4.1 Overview

Logit takeover prediction models are probabilistic models as they model the probability (between 0 and 1) that a firm will receive a bid during the specified period. Determining whether the computed takeover probability is high enough for a firm to be considered a potential target has remained a major challenge to researchers. This section examines and critiques the methods that have been used by different researchers. It also highlights the potential sources of bias in the different methods and proposes ways in which the bias can be mitigated.

2.6.4.2 Cut-off probabilities for identifying future targets

Three main empirical techniques for identifying the optimal cut-off have been proposed by Palepu (1986), Barnes (1990) and Powell (2001). Palepu (1986) contends that the optimum cut-off probability to be employed should depend on 'prior probabilities of takeover, the decision context of interest and the appropriate pay-off function' (p. 12). Palepu (1986) derived his optimal takeover probability as the point at which the probability density function of targets is equal to the probability density function of non-targets. This methodology aims to minimise the overall sample error rate as it assumes that the cost of type I and type II errors are equal. This technique has been used by other studies including Espahbodi and Espahbodi (2003).

Palepu's (1986) estimation sample consists of an average of 18 targets a year over a period of nine years. The population of non-target firms at the end of the nine-year period is 2,054, meaning that only about 7.3% of firms in the period actually received a bid. Palepu's cut-off methodology nonetheless led him to predict that 625 firms of 1,117 firms in the holdout sample (i.e. over 56% of the holdout sample) will receive a bid in 1980. This immediately highlights the inefficiency in this methodology given the discrepancy between past experience of 18 targets a year (between 1971 and 1979) and the prediction of 625 targets in one year (1980).

Barnes (1998) and Powell (2001) discuss the limitations of Palepu's 'equal cost of type I and type II errors' assumption and propose the use of an alternative cut-off point which maximises the return for investors. This coincides with the cut-off probability that maximises the concentration of targets within the predicted target portfolio. This assumption leads to the selection of a higher cut-off probability compared to the one arrived at using Palepu's method. Barnes (1999) show that the Barnes (1998) methodology when applied to Palepu's results increased Palepu's cut-off probability from 0.112 to 0.30. This will lead to the prediction of a smaller number of firms than the 625 potential targets predicted by Palepu. Although it is not certain if such an increase in the cut-off point will lead to better target concentrations, this methodology (employed in Barnes (1998, 1999) and Powell (2001) to identify a suitable cut-off), appears to be more efficient from an investment stance point when compared to Palepu's method. The methodology will therefore be employed in the current study. The method (and its underlying rationale) is fully discussed in chapter 4.

2.6.4.3 Percentiles, Deciles and Quintiles (fixed portfolios) for portfolio selection

Some recent studies such as Brar et al. (2009) and Cremers et al. (2009) have used deciles and quintiles in preference to cut-off probabilities in the identification of potential targets. These studies simply consider the top 10% (Brar et al. (2009) and Cremers et al. (2009)) or 20% (Cremers et al. (2009)) of firms with highest probabilities as their sample of predicted targets. While this appears to be a conventional methodology in other areas of finance, it is, potentially, problematic as it implicitly assumes that 10.00% or 20.00% (respectively) of the firms in the sample are expected to receive a bid in the period, on average[72]. The long run average number of UK listed firms within the FTSE All-Share receiving a bid each year is about 5.28% as will be shown in chapter 5. Under the decile and quintile schemes, a perfect model will, on average, achieve type II errors of 47.20% (when deciles are used) or 73.60% (when quintiles are used)[73]. Given *a posteriori* knowledge of a 5.28% rate of takeover activity, it seems more reasonable to forecast that in each year the 5.28% of firms with highest takeover probability are the most likely targets. That is, all firms with takeover probability above the 95th percentile are potential targets. This only partly resolves the issue.

Perhaps, the limitation of using quintiles, deciles and percentiles for predicting future targets is the fact that to decide whether or not a firm is a potential target requires the modeller to compute the takeover probability for every firm in the population. This poses a

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[72] Palepu (1986) argues that, on average, less than 3% of US listed firms receive a bid every year.

[73] When deciles are employed (for example) a perfect model will correctly predict all targets (5.28% of the population) but also predict non-targets as targets (type II errors), in order to attain the 10% decile cut-off. Hence, 4.72% of the 10% of firms predicted as targets will constitute a misclassification, leading to a type II error of 47.20%.

problem in a setting where data for different firms become available at different time periods[74]. This is not the case when cut-offs are employed. Here, each firm's takeover probability can be computed as soon as its data is available and its probability directly compared against the cut-off to determine whether or not the firm is likely to receive a bid. Another problem with the use of deciles and quintiles is that they do not allow for flexibility from one year to another. Studies in the merger wave literature (see, for example, Harford (2005)) show that the level of takeover activity significantly changes from one period to another. The use of deciles or quintiles do not account for the changes in the level of takeover activity from one year to the next.

2.6.4.4 Summary

This section has shown that several techniques for identifying future targets out-of-sample have been used in the literature. The different techniques appear to have different merits and demerits. To my knowledge, no study has examined the impact of using these different techniques on the results of prediction tests. This issue is partly addressed in this study. As will be shown in chapter 6, these techniques lead to different results. Hence, the reported performance of a model can be biased by the techniques used to identify the optimal portfolio. Therefore, an unbiased approach to testing, perhaps, employs a cross section of methodologies. The use of a cross section of methodologies (e.g., cut-offs, deciles, quintiles and percentiles) will allow for the impact of methodological choice to be averaged-out and the unbiased predictive ability of the model ascertained. This approach is adopted in this study. This is further discussed in chapter 4.

2.6.5 Prediction hypotheses and variable selection methods

2.6.5.1 Overview

The 'Garbage in, Garbage out' principle, a popular aphorism in the field of information and communication technology, specifies that a model is only as good as the quality of its input data. This highlights the importance of selecting appropriate explanatory variables for prediction modelling. This section discusses the approaches to selecting explanatory variables in prior research, as well as, the variables and hypotheses that have been employed in the literature.

[74] For example, different firms have different financial year ends, implying that firm data will be made public at different points in time. In the context of deciles (for example), the top-10 highest takeover likelihood firms can only be identified once the financial data for all firms are made public.

2.6.5.2 Prediction hypotheses

The selection of appropriate explanatory variables for inclusion in prediction models remains a challenge in prediction modelling research. The problem in predicting targets lies with identifying the best explanatory/predictive variables (Barnes (2000)). The studies in the first era (1968–1985) and some of the studies in the second era do not generally discuss the theoretical motivation for their choice of prediction variables. The general approach employed by these studies involves the use of univariate analysis (difference of means tests between targets and non-targets) to identify significant variables from a set of all available variables. Prior studies such as Simkowitz and Monroe (1971) and Cahan et al. (2011) have employed a 'kitchen-sink' approach to variable selection. Some studies use other variable reduction methods such as stepwise regression analysis (as in Simkowitz and Monroe (1971) and Espahbodi and Espahbodi (2003)) and factor analysis[75] (as in Barnes (1990)) to identify the important explanatory variables or reduce the variables to meaningful constructs.

Palepu (1986) proposes a theoretical framework for the selection of hypotheses for takeover prediction. In his study, Palepu (1986) argued that a set of six hypotheses[76] can sufficiently explain the motivations for and choice of target selection. These hypotheses include: management inefficiency, growth-resource mismatch, undervaluation, price earnings magic, industry disturbance and firm size hypotheses (fully discussed in chapter 3). As discussed in section 2.5.3 and 2.5.4, these hypotheses have been replicated across many post-Palepu studies. Two more hypotheses, including tangible property hypothesis (proposed by Ambrose and Megginson (1992)) and the free cash flow hypothesis (proposed by Powell (1997) and based on Jensen's (1986) agency cost of free cash flow theory), have been proposed and used extensively in the prediction of takeover targets. Brar et al. (2009) include firm age as a variable for prediction. The researchers neither discuss the rationale for using firm age nor empirically test its validity as an explanatory variable.

Despite the advancement of these hypotheses, there is a near consensus amongst researchers that little is known about the characteristics of targets – suitable explanatory variables for takeover likelihood modelling. As discussed in section 2.5.3, Ambrose and

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[75] By grouping the variables into factors, factor analysis helps curb the problem of multicollinearity which arises when variables are indiscriminately included in the prediction model.

[76] Management inefficiency, growth-resource mismatch, undervaluation, price earnings magic, industry disturbance and firm size hypotheses.

Megginson (1992), for example, finds no support for any of Palepu's hypotheses. This finding is more disconcerting given that the two studies employ a US sample with data drawn from around the same period. One possible reason for this finding is the fact that Palepu (1986) ignores the institutional context (the effect of takeover defences and antitakeover amendments) which Ambrose and Megginson attempt to capture. Nonetheless, this does not explain the full story as Palepu's variables remain insignificant when institutional variables are excluded from the Ambrose and Megginson (1992) model. Other non-US studies (such as Powell (1997, 2001, 2004), Barnes (1998, 1999, 2000), Powell and Yawson (2007) and Brar et al. (2009)) have failed to find evidence consistent with some of Palepu's hypotheses.

It appears the set of eight hypotheses used in prior research is limited and do not fully capture the complexity of the M&A target selection decision. For example, Powell and Yawson (2007) show that these same (six to eight) hypotheses could be used to model other restructuring activities including bankruptcies, divestitures and layoffs. Their results show that the old hypotheses better explain divestitures and layoffs, than takeovers. This evidence suggests that a timely redevelopment of takeover prediction hypotheses is warranted. This is a gap which this research aims to address. A contribution of this thesis is to develop a broader set of prediction hypotheses based on a more expansive theoretical foundation. As will be shown in chapter 5, this expansion leads to the development of a more powerful model.

2.6.5.3 Proxies for prediction hypotheses

The selection of suitable proxies for hypotheses is also a key issue for researchers. Concepts such as management inefficiency (or firm performance) and firm size can be measured in different ways as there is no theoretical guidance on the selection of proxies for hypotheses. Different researchers have employed different proxies for management inefficiency including return on assets (Palepu (1986)), return on equity (Palepu (1986), Brar et al. (2009)), stock abnormal return (Palepu (1986), Ambrose and Megginson (1992)), operating profit margin (Powell (1997), Brar et al. (2009)), sales growth (Brar et al. (2009)) and earnings growth (Brar et al. (2009)). Different proxies such as market capitalisation (Brar et al. (2009)), net book value of assets (Palepu (1986), Espahbodi and Espahbodi (2003)), total sales (Brar et al. (2009)), total assets (Powell (1997)) and number of employees (Brar et al. (2009)) have also been used to measure firm size. It is popular to see researchers combining different proxies to test a single hypothesis.

Given the likely high correlation between some of these proxies (which results in the problem of multicollinearity), and the need to manage the degrees of freedom in the model, researchers turn to select only a few proxies for each hypothesis. It is, therefore, unlikely that all the dimensions of a hypothesis will be captured by selected proxies. The choice of proxy is therefore critical as different proxies are likely to yield different results in some cases. Powell (1997), for example, argues that some of the proxies used in his study might have poorly operationalised the underlying concepts or hypotheses. Without the use of data mining techniques such as stepwise regressions, the issue of selecting the most efficient proxies remains a challenge to address. The selection of suitable proxies in this study is further discussed in chapter 3.

2.6.5.4 Raw versus industry-adjusted financial ratios

There is no consensus on the choice between raw versus industry-relative financial ratios in selecting appropriate proxies for hypotheses. Barnes (1990) notes that financial ratios are more likely to be skewed than normally distributed and are therefore not suited for use in models such as LDA which assume that independent variables are normally distributed. This is, perhaps, not a major problem when using logit regression models. Barnes (1990) proposes the use of industry-relative variables as a way of normalising firm financial variables and meeting the assumptions of the LDA technique. From an empirical stance, Pasiouras (2007) contends that industry-relative financial ratios have more explanatory power when compared to non-industry-adjusted firm variables. Cudd and Duggal (2000) also argue that different industries have specific distributional characteristics of their financial ratios. They advocate that financial ratios used in prediction modelling should, therefore, be adjusted for industry specific characteristics. Nonetheless, the argument for industry-adjustment advanced in Cudd and Duggal (2000) is not empirically supported, as they find that the unadjusted model has a slightly higher explanatory power when compared to the industry-adjusted model.

Few studies (such as Brar et al. (2009)) have used industry-adjusted ratios in developing takeover prediction models. Some studies (such as Palepu (1986)) focus on a few industries (mining and manufacturing) thus eliminating a need to employ industry-adjusted financial ratios. The use of industry-adjusted ratios is well suited for model development as the model is developed using past data which is available for all firms and all industries. Nonetheless, the use of industry ratios is, perhaps, ill-suited for out-of-sample testing and real life model application and is likely to introduce some look-ahead bias in prediction model testing. This can be explained as follows.

In a practical setting, an investor relying on target prediction models will determine whether a firm is a suitable target or not as soon as its financial results are released. This will be accomplished by comparing the firm's takeover probability (based on its published financial results) against a set criterion (cut-off or a benchmark probability). Different firms within the same industry have different financial year-ends. This implies that the industry ratio cannot be computed unless all firms within the industry have published their financial results. Employing industry-adjusted ratios in out-of-sample prediction implicitly assumes that all firms within the industry release their financial statements at about the same time or portfolios of predicted targets are formed only after the financial results of all firms in all industries are publicly available. One way of overcoming the problem is to use the previous year's industry average in computing the firm's industry-adjusted ratio in the current year. This, nonetheless, assumes that industry ratios are stable from one year to another.

Given the potential importance of controlling for industry differences and the need to avoid look-ahead bias in prediction, the approach employed in the current study is to use industry dummy variables as opposed to industry-adjusted variables as control variables in the model[77]. Using industry dummies, eliminates the need to distort financial data, mitigates the problem of look-ahead bias in out-of-sample prediction and ensures that industry differences in the distribution of financial variables are controlled for.

2.6.5.5 Summary

Section 2.6.5 has highlighted the 8 key hypotheses used across the takeover prediction literature as well as the limitations inherent in this set of hypotheses. These discussions are continued in chapter 3. This section has also noted the diversity in approaches for selecting prediction hypotheses and the challenges researchers face when selecting suitable proxies for these hypotheses. The issue of using industry-adjusted ratios as opposed to unadjusted firm ratios is discussed and a potential source of look-ahead bias is identified. The use of industry dummies (as opposed to industry-adjusted firm ratios) is advanced as a potentially

[77] Consistent with prior studies (e.g., Brar et al. (2009)), the objective of contrecursive for industry effects is not to explain industry differences in takeover likelihood but to manage the distributional differences in the financial characteristics of firms across different industries. As will be discussed in chapter 5, the use of industry dummies does not affect the results and therefore to allow for simplicity industry dummies are subsequently excluded from the model.

more analytically tractable alternative for controlling for industry distributional characteristics of financial ratios.

2.7 Chapter summary and conclusion

This literature review chapter discusses the relevance of takeover prediction modelling to different stakeholders (including managers, investors, policy makers and researchers) as well as its implications to theory (such as the efficient market hypothesis and the market anticipation versus insider trading debate). The chapter reviews the historical development of the takeover prediction literature across time and across different contexts or countries – mainly the UK and the US. The literature is broken down into three eras, with studies published during each era sharing several similarities in approach and methodology.

The studies in the first era (1968–1985) mainly focus on defining the characteristics of targets and bidders. These studies adopt simple methods (such as difference of means testing and linear discriminant analysis) to identify some of the defining the characteristics of targets. A key limitation of these studies is the lack of a theoretical rationale to underlie the variable selection process. As such, these studies are only able to identify (but not explain) the differences between in financial characteristics between targets and non-targets. Led by Palepu (1986), the studies in the second era (1986–2002) focus on hypotheses (or theory) development as well as the application of more robust methods in testing the power of prediction models[78]. Studies during this era build upon the Palepu (1986) framework by proposing other methodological amendments such as new hypotheses (e.g., Ambrose and Megginson (1992) and Powell (1997)) and new ways of computing cut-off probabilities (e.g., Barnes (1999) and Powell (2001)). The studies in the third era (2003–2013) mainly focus on evaluating the discriminatory ability of different types of models (e.g., parametric and non-parametric), with very few of these studies attempting to actually predict future targets. Building on the studies in the second era, Powell (2004) and Powell and Yawson (2007) introduce two different multinomial frameworks for takeover prediction. Their empirical evidence, however, undermines their arguments as there is no evidence that the multinomial model substantially improves upon the binomial model.

[78] These tests involved both out-of-sample prediction ability and the ability to generate abnormal returns.

Not surprisingly, investment practitioners have also been involved in the development and use of prediction models. Models used by two major investment professionals – Morgan Stanley and Deutsche Bank – are discussed in this review. The models advanced by the two institutions are markedly different. On the one hand, Morgan Stanley employs a simple rank-based methodology which sorts stocks based on how they perform across five financial ratios. In contrast, strategists at Deutsche Bank employ a sophisticated high-frequency 'quant-based' model which predicts targets on a monthly basis. The results from these publications reveal that neither method consistently outperforms the market. In fact, the two models substantially underperform the market in out-of-sample tests. The results from the Deutsche Bank report questions the use of high-frequency data, particularly, as there is no underlying reason why such data should drive the takeover decision. Further, the research applies a monthly rebalancing framework but provides no evidence that more frequent rebalancing improves the chances of generating abnormal returns from target prediction.

With the exception of a few US studies incorporating corporate governance measures in their models (e.g., Espahbodi and Espahbodi (2003) and Cremers et al. (2009)), there is very little emphasis or consideration of the potential uniqueness of context (including the USA, the UK, Canada and the European Union) across different studies. As discussed in section 1.3, the regulation of takeovers varies across countries. Presumably, this has an impact on what factors drive the strategic takeover decision in these countries. Nonetheless, little has been said about the influence of context on the process and framework for takeover prediction modelling. This issue is partly addressed in this study through the development of new hypotheses (which reflect the UK context) and the reassessment of prior prediction hypotheses (further discussed in chapter 3).

The final part of the chapter is a critique of the methodological choices of prior empirical studies. Four key choices (including, the choice of discriminatory model (parametric or non-parametric), the choice of sample construction technique, the choice of cut-off probability (or technique for identifying targets out-of-sample) and the choice of prediction hypotheses and proxies), are discussed. A review suggests that the logit model (parametric model) is, perhaps, an optimal choice when the goal of a researcher is both to explain and to predict. Its attractiveness lies in the fact that its assumptions are less restrictive than those of other models and it is theoretically suited for takeover prediction modelling. The probit model bears the same qualities but is slightly less popular amongst researchers in takeover likelihood modelling.

Sampling remains a major challenge due to the rare event problem. Several researchers in all three eras rely on non-random sampling techniques which aim to improve the information content of the sample. Nonetheless, it is probable that the use of these non-random sampling techniques introduces bias in model testing and results in poor out-of-sample model performance. There is little consensus on the appropriate technique for identifying a suitable cut-off probability. I examine the merits of different methods and highlight the possibility that the use of any one technique can constitute a source of bias in model testing given that results are likely to vary with the technique for selecting cut-off probabilities. The use of a cross section of techniques (as opposed to any single technique) is likely to be a more optimal (or robust) approach.

With little exception, prior studies have adopted the hypotheses put forward by Palepu (1986), Ambrose and Megginson (1992) and Powell (1997). Notwithstanding, several post-Palepu (1986) studies find no evidence to support some of the Palepu hypotheses. In fact, Ambrose and Megginson (1992) and Powell (2001) directly question the validity of the hypotheses proposed by Palepu (1986). These studies have reiterated the need to fully understand the strategic rationale for target selection. This area constitutes a major gap in the research area which this thesis partly addresses. The next chapter (chapter 3) is the hypotheses development chapter. This study advances the literature by redeveloping the Palepu (1986) hypotheses and by introducing new hypotheses for takeover prediction modelling. The chapter starts by reviewing key theories explaining why mergers and acquisitions occur and why certain targets are selected by bidders. This theoretical review constitutes the basis for redeveloping the old hypotheses and introducing the new hypotheses. The hypotheses presented in chapter 3 are tested in chapter 5.

CHAPTER 3 PREDICTION HYPOTHESES

3.1 Overview

The previous chapter reviewed the empirical literature on takeover target prediction. It discussed the motivations for takeover prediction modelling and reviewed the historical development of the literature. The chapter critiqued the Palepu (1986) approach, which has been widely adopted by prior researchers, by highlighting potential sources of bias inherent in his methodology for takeover prediction. One key limitation of prior research, as was noted in chapter 2, is the use of a limited set of six to eight hypotheses for takeover prediction in many studies. I argue that prior studies rely on a limited set of prediction hypotheses which, perhaps, do not fully explain why many firms receive takeover bids. This particular limitation – the irrelevance and lack of comprehensiveness of takeover prediction hypotheses – is also highlighted in studies such as Powell (1997), Ambrose and Megginson (1992) and Powell and Yawson (2007), amongst others. Nonetheless, little has been done to improve the hypothesis development framework for takeover prediction.

This study contributes to the literature by reviewing (and redeveloping) some of the key hypotheses proposed by Palepu (1986) as well as proposing some new theory-grounded takeover prediction hypotheses. The hypotheses developed in this study are described as 'new' because they have not been used by prior studies to predict takeover targets. The hypotheses build on established research in other areas of accounting and finance. This chapter reviews the theoretical framework underlying takeover prediction hypotheses, both newly developed ('new') hypotheses and the ('old') hypotheses used in prior studies. Some of the hypotheses introduced by prior research are also redeveloped[79] in this chapter to provide new insights and new predictions for firm takeover likelihood modelling. The rest of the hypotheses introduced by Palepu (1986), Ambrose and Megginson (1992) and Powell (1997) are restated in line with their original predictions.

The old hypotheses for takeover prediction are discussed in section 3.2. The new hypotheses introduced in this study as well as the old hypotheses which are redeveloped in this study are discussed in section 3.3. The key proxies and the constituent variables that

[79] One of such hypotheses is the firm size hypothesis. Prior research has presumed that takeover likelihood is declining in firm size. It is proposed here that the relationship between takeover likelihood and firm size is nonlinear – an inverted U-shaped relationship.

are used to operationalise the old and new hypotheses are also discussed in this chapter. As will be further discussed in chapter 4, financial data for all firms in the sample is obtained from Thomson DataStream while data on takeover activity is obtained from Thomson OneBanker. The DataStream codes for the proxy variables are noted (in this chapter) in box brackets, i.e., '[DataStream code]'. The exact time period over which the data is collected, the matching and realignment of the data from the two databases, the development of a unique database to meet the objective of this study and other methodological considerations (e.g., industry definitions) are discussed in chapter 4.

3.2 Old hypotheses for takeover target prediction

3.2.1 Overview

The focus of takeover prediction hypotheses development is to identify some of the characteristics of firms which increase their likelihood of receiving takeover bids. Researchers (including Barnes (2000) and Palepu (1986)) emphasise the importance of the choice of prediction variables in the development of effective prediction models. Palepu (1986) proposes six hypotheses for the prediction of future takeover targets. These include: inefficient management, firm undervaluation, industry disturbance, growth-resource mismatch, firm size, and price-earnings[80]. The use of these hypotheses has been consistent amongst researchers. Powell (1997) and Ambrose and Megginson (1992) propose two additional hypotheses for takeover prediction, including the free cash flow hypothesis (Powell (1997)) and the tangible assets hypothesis (Ambrose and Megginson (1992)). With the exception of firm size and firm age these old hypotheses are adopted in the current study. The firm size and firm age hypotheses (used in prior studies such as Palepu (1986) and Brar et al. (2009), respectively) are redeveloped (in section 3.3) to yield new insights on their relationship with takeover likelihood. The discussion of the hypotheses is organised as follows: inefficient management (section 3.2.2), firm undervaluation (section 3.2.3), industry disturbance (section 3.2.4), free cash flow (section 3.2.5), growth-resource mismatch (section 3.2.6), tangible assets (section 3.2.7), firm size (section 3.2.8) and firm age (section 3.2.2).

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[80] P/E and undervaluation hypotheses have a similar theoretical underpinning and are therefore combined in later discussions. Prior studies have treated the two hypotheses as independent.

3.2.2 Management inefficiency hypothesis

Target management inefficiency has been frequently cited as a main rationale for takeovers[81]. Palepu (1986) advances the inefficient management hypothesis as a key hypothesis for takeover prediction. The hypothesis stipulates that an underperforming management team is likely to face a control contest from a more efficient management team, which seeks to generate value for shareholders through improved management of shareholder resources. As noted above, the hypothesis has been widely adopted across the takeover prediction literature. It builds on the agency theory and the market for corporate control concept.

Agency theory posits that the separation between the principal and the agent and the inherent information asymmetry between the two parties, potentially, gives rise to conflicts of interest. Conflicts arise as the agent has an incentive to expropriate the wealth of the principal in order to maximise his utility (Jensen and Meckling (1976)). In the face of this conflict of interest, the principal puts in place several mechanisms (such as pay-for-performance contracts, board oversight, internal controls and independent audits, amongst others), which focus on safeguarding his interest or realigning the agent's interest with the principal's. Based on Manne (1965), Jensen and Ruback (1983) introduce the concept of 'the market for corporate control' (MCC) as an external monitoring mechanism for monitoring management action. This market (also referred to as the takeover market) is one in which various management teams compete for the rights to manage a firm's resources (Manne (1965) and Jensen and Ruback (1983)). Manne (1965) contends that the takeover market makes the corporate world a more efficient one by ensuring that managers who deviate from the best interest of their shareholders are replaced by more efficient management teams[82].

The role of the takeover market in enforcing managerial discipline is, possibly, weakened by the existence of other disciplinary mechanisms such as industry competition (product-market competition), corporate governance mechanisms, competition within the

[81] See, for example, Manne (1965), Jensen and Ruback (1983), Grossman and Hart (1980), Jensen (1988) and Morck et al. (1989), amongst others.

[82] This theory is also consistent with the undervaluation theory. The market value of the firm reflects the management's capacity to generate future cash flows using the firm's assets. A firm with poor management is therefore likely to have a lower value than it would have, if it had a good management team. In line with the firm undervaluation theory of takeovers, a new management team perceives such a firm as being undervalued and therefore a suitable target. This is further discussed in section 3.2.3.

managerial labour market and threat of bankruptcies and liquidation (Jensen and Meckling (1976)). The role of the takeover market as a disciplinary mechanism is further questioned given investors ability to easily transfer their investments from poorly performing to well performing firms. The management inefficiency hypothesis will be irrelevant if takeovers do not serve a disciplinary role as posited by the market for corporate control (MCC) theory.

It can be argued that the evidence, with regards to the existence of the market for corporate control, is mixed and inconclusive. The MCC theory has been tested in the event study literature by researchers looking at the performance of merger targets prior to merger bids. Studies in the event study literature either find no support for or evidence against the inefficient management hypothesis. See, for example, Dodd and Ruback (1977), Mandelker (1974), Langetieg (1978), Malatesta (1983), Asquith and Kim (1982), Franks and Mayer (1996), Agrawal and Walkling (1994) and Agrawal and Jaffe (2003). Researchers generally find that targets earn negative but insignificant abnormal returns (Mandelker (1974)), zero returns (Langetieg (1978)) and positive abnormal returns (Dodd and Ruback (1977)) in the period prior to acquisitions. This position (no support for the MCC theory) has been corroborated by studies looking at accounting performance. Berger and Ofek (1996), for example, find that a firm's return on equity ratio does not affect its probability of being acquired. From an extensive literature review and an empirical study looking at both target accounting and stock market performance, Agrawal and Jaffe (2003) concludes that there is little evidence to support the assertion that underperforming firms are more likely to become takeover targets.

Notwithstanding, some contradictory empirical evidence supports the existence of a thriving MCC (see, for example, Shrieves and Stevens (1979), Asquith (1983) Hasbrouck (1985), Morck et al. (1988) and Lang et al. (1989)). Asquith (1983), for example, finds that targets underperform prior to takeover bids. The cumulative abnormal returns of targets between 'day –480' to 'day –60' prior to the takeover announcement is –14.8% on average (Asquith (1983)). Again, Shrieves and Stevens (1979) find that 15.2% of 112 takeover targets in their sample can be classified as 'bankrupt' at the time of acquisition. In support, Hasbrouck (1985), Morck et al. (1988) and Lang et al. (1989) report that targets have significantly lower Tobin's Qs which declines year-on-year – with the probability of hostile takeover generally decreasing with a firm's Q ratio. Using empirical evidence from the takeover market, Grossman and Hart (1980), Jensen (1988) and Morck et al. (1989)

conclude that shareholders benefit from takeovers due to the replacement of inefficient management. These studies provide contradictory evidence which supports the view that an efficient MCC exists and acts to replace inefficient management teams.

The management inefficiency hypothesis has been directly tested in the takeover prediction literature. The evidence from this literature is also inconclusive. In support of the MCC and the management inefficiency hypothesis, some researchers find that targets have lower accounting performance (see, for example, Barnes (1999), Pasiouras (2007), Ouzounis et al. (2009)) and lower stock market performance (Powell and Yawson (2007)). Others find no significant difference between targets and non-targets in terms of accounting profitability and stock market performance (e.g., Ambrose and Megginson (1992) and Powell (1997)). Some researchers report mixed results from the same sample. Palepu (1986), for example, finds that takeover likelihood decreases with a firm's stock market returns but increases with its accounting return. Brar et al. (2009) show that takeover likelihood increases with accounting profitability but declines with sales growth. These findings (Palepu (1986) and Brar et al. (2009)) neither support nor contradict the predictions of the MCC hypothesis.

While it is generally hypothesised that poor management performance can lead to takeovers, there is no consensus on what constitutes 'poor management performance'. The mixed findings appear to be a result of the use of different performance proxies (both accounting and market-based) across different studies, without clarity on what these proxies measure. Several measures of performance, including accounting profitability (return on assets, return on sales, operating profit margins) and market performance (stock return) have been employed across the literature. While market performance measures are thought to measure the present value of all future cash flows that will accrue to a particular stock as a result of the manager's actions (Lambert and Larcker (1987)), accounting measures have been criticised for being unable to reflect the future consequences of current managerial actions (Rappaport (1986)). In line with Rappaport (1986), Lambert and Larcker (1987) argue that accounting regulations (such as the US GAAP and IFRS) may limit the ability of accounting performance to reflect future cash flows that a firm may generate as a result of current management actions. The two measures of management performance can, perhaps, be considered as complements (not substitutes), as accounting measures mainly gauge management's historical performance while market measures, perhaps, assess management's future prospects.

Much of the evidence points to the possibility that bidders show a preference for targets with potential for profitability. There is overwhelming evidence that, on average, targets are profitable firms – as shown by their accounting performance (Palepu (1986), Brar et al. (2009) and De and Jindra (2012)). The evidence also suggests that, despite current profitability, targets have a lower prospect for future growth or a limited ability to generate future cash flows. This is corroborated by findings that targets face declining sales growth and declining stock returns prior to receiving a bid (Brar et al. (2009), Powell and Yawson (2007), Palepu (1986)). In this sense, the management inefficiency hypothesis in takeover prediction is, perhaps, too general to be meaningful in building the profile of a takeover target. Perhaps, the management inefficiency hypothesis can better be understood as management's inability to sustain positive growth in future cash flows for shareholders, despite current profitability. This qualification of the hypothesis is tested in the current study by investigating both the accounting and stock market performance of targets in comparison to non-targets. In line with Palepu (1986), the hypothesis, as adopted in the current study, is stated as follows.

> ***Hypothesis 1: Ceteris paribus, the probability that a firm will become the subject of a takeover bid decreases as its performance increases.***

As in prior studies, accounting and market measures of performance are used to capture the two dimensions of management performance – historical (accounting) and future (market). In line with prior studies (such as Palepu (1986), Brar et al. (2009), amongst others), the return on capital employed (ROCE) and the average daily abnormal return (ADAR) over the last year is used to measure market performance. Return on capital employed is computed as the ratio of net operating income before tax and depreciation or EBITDA [wc01250] to total capital employed [wc03998]. This ratio measures management's ability to utilise resources efficiently in the generation of profits through regular business operations.

Additionally, I add a new proxy – a loss-making dummy variable (denoted LMDummy) – to directly test whether poor accounting performance (i.e., reporting a loss) increases a firm's takeover likelihood. The LMDummy takes a value of 1 when a firm reports negative net earnings [wc017151] in a specific year and a value of 0, otherwise.

The market measure of management performance is the average daily abnormal return (ADAR) – a measure of stock performance. ADAR represents the average of the 260 observations of daily abnormal returns (DAR) of the stock. DAR is computed from daily price index data [RI] using the OLS market model (discussed in Brown and Warner (1980, 1985)). The model for the computation of the DAR is given as follows;

$$DAR_{it} = R_{it} - \left(\hat{\propto}_i + \hat{\beta}_i R_{mt}\right) \dots\dots\dots Eqn\ 3.2.2\ (1)$$

Here, DAR for a firm *i* at time *t* is given by the difference between the firm's actual stock return at time *t* (R_{it}) and its expected stock returns at time *t* $\left(\hat{\propto}_i + \hat{\beta}_i R_{mt}\right)$. The returns for each firm *i* on day *t* (denoted R_{it}) and the market *m* on day *t* (denoted R_{mt}) are first computed from adjusted price [RI] as follows.

$$R_{it} = (RI_{it} - RI_{it-1})/(RI_{it-1}) \dots\dots\dots Eqn\ 3.2.2\ (2)$$

$$R_{mt} = (RI_{mt} - RI_{mt-1})/(RI_{mt-1}) \dots\dots\dots Eqn\ 3.2.2\ (3)$$

The daily return of the FTSE All-Share (R_{mt}) is used as a proxy for the daily market returns. Next, $\hat{\propto}_i$ and $\hat{\beta}_i$ are estimated by using data in the previous period (260 trading days). Each firm's daily stock returns in period *T-1* (previous period)[83] is regressed on its daily market returns in period *T-1* and the coefficients of the regression model are used as estimates of $\hat{\propto}_i$ and $\hat{\beta}_i$. The regression coefficients ($\hat{\propto}_i$ and $\hat{\beta}_i$ estimates) from period *T-1* are used to compute ADAR in the next period (period *T*).

$$ADAR_{iT} = \frac{1}{260}\sum DAR_{it} \dots\dots\dots\dots\dots Eqn\ 3.2.2\ (4)$$

As will be fully discussed in chapter 4, the June approach to portfolio development is adopted in this study. This implies that portfolios are formed from 1st July each year and held to 30th June in the next year. To compute a firm's ADAR on 1st July 2010, for example, I use its daily return data from 1st July 2008 to 30th June 2009 to generate its $\hat{\propto}_i$ and $\hat{\beta}_i$ estimates. I then use these estimates together with its daily return data from 1st July 2009 to 30th June 2010 to compute its DAR (as per equation 3.2.2(1)). The 260 DAR observations are then averaged to obtain its ADAR for the period from 1st July 2009 to 30th June 2010. As per the hypothesis, I expect takeover probability to decline with ADAR.

[83] As will be fully discussed in chapter 5, each period is considered to run from 1st July year 1 to 30th June year 2.

3.2.3 Firm undervaluation hypothesis

The valuation theory of mergers contends that mergers are perpetrated by bidders who either (1) hold private information about the true value of the target or (2) hold private information on how a higher value can be realised for the target (Trautwein (1990)). The misvaluation hypothesis (Shleifer and Vishny (2003) and Dong et al. (2006)), which builds on this theory, suggests that the stock market's inefficiency in the valuation of firms has important effects on takeover activity. As suggested by Dong et al. (2006), the effects arise from the bidders' deliberate efforts to 'profit by buying undervalued targets for cash at a price below fundamental value, or by paying equity for targets that, even if overvalued, are less overvalued than the bidder' (p. 726). Studies such as Ang and Cheng (2006), Dong et al. (2006) and Bi and Gregory (2011) have investigated how misvaluation (either overvaluation or undervaluation) of both targets and bidders moderates takeover decisions.

In the prediction of takeover targets, no assumptions are made about the characteristics of the respective bidders. If this is the case, on average, an overvalued firm is unlikely to be an attractive target to the average bidder – a bidder who is not highly overvalued. Studies in takeover prediction therefore focus on undervaluation of firms as a driver of takeovers – the undervaluation hypothesis. This hypothesis predicts that firms perceived as relatively undervalued will be attractive takeover targets to the average bidder (Belkaoui (1978)). The idea is supported by the valuation theory of mergers (Trautwein (1990)). The theory holds that mergers are perpetrated by bidders who have superior (private) information about the target not available to the market. Such private information could include future cash flow forecasts and methods for improving such cash flows. A management team (prospective bidder) with private information about another firm (a prospective target) will have a higher valuation for this firm compared to the firm's current market value. The prospective target thus appears undervalued and, therefore, a 'cheap buy' for a rational wealth maximising bidder (Palepu (1986)).

Several studies have evaluated whether firm undervaluation explains takeover propensity[84]. Hasbrouck (1985) finds that the MTB of a firm is inversely related to the firm's takeover likelihood. Hasbrouck (1985) also argues that low MTB is indicative of managerial

[84] While Tobin's Q has been proposed as a measure of firm undervaluation, it is usually proxied by the market to book ratio due to the unavailability of asset replace costs (e.g., Hasbrouck (1985)). Hasbrouck (1985) notes that low MTB indicates that a firm is under-priced as its assets are worth more than its market value.

inefficiency and therefore an opportunity for value to be derived through better management. Other empirical studies (including, Palepu (1986), Morck et al. (1989), Martin and McConnell (1991), Walter (1994) and Powell (1997)) have shown that takeover likelihood declines with a firm's MTB. Walter (1994) finds that MTB is the most important ratio when differentiating between targets and non-targets. In line with the literature, the hypothesis is stated as follows.

> ***Hypothesis 2: Ceteris paribus, takeover probability increases with the level of firm undervaluation.***

Prior literature uses the price to book value of equity (MTB) ratio as a measure of firm undervaluation, misvaluation or overvaluation (see for example, Palepu (1986), Ambrose and Megginson (1992), Powell (1997, 2001), Powell and Yawson (2007), Dong et al. (2006) and Brar et al. (2009)). As argued by Dong et al. (2006), to the extent that the book values of equity measure the value of a firm, any discrepancies between book and market values of equity will capture the market's efficiency in valuing the firm. This suggests that MTB ratios of 1 indicate correct valuation and any deviation from this value will suggest misevaluation. Consistent with prior studies, the MTB (ratio of market value of equity to book value of equity) is used to proxy for firm undervaluation in this study. To improve analytical tractability, the inverse of MTB (i.e., the book to market value of equity ratio – BTM) is used in preference to the traditional MTB ratios[85]. As per Dong et al. (2006), high (low) BTM ratio indicates that the firm is relatively undervalued (overvalued).

Powell and Yawson (2007) compute book value of equity as the equity capital and reserves (305 or WC03501) minus total intangibles (344 or WC02649) and market value of equity as the number of shares outstanding [NOSH] multiplied by share price [UP]. This definition is adopted in this study as the BTM ratio is defined as;

$$BTMratio = \frac{Bookvalue\ of\ Equity}{Marketvalue\ of\ Equity} \ldots\ldots\ldots Eqn\ 3.2.3\ (1)$$

Where:

$Bookvalue = [WC03501] - [WC02649] \ldots\ldots\ldots Eqn\ 3.2.3\ (2)$

$MarketValue = [NOSH] * [UP] \ldots\ldots\ldots Eqn\ 3.2.3\ (3)$

[85] Negative book values can potentially distort the inference drawn from MTB but not from BTM ratios.

As will be discussed in chapter 4, the June approach is adopted in matching firm financial data (e.g., book value) to market data (e.g., market value). Here, book values for any financial year-end between January and December year *t* are matched to market values on 30 June year *t+1*.

Brown et al. (2008) contend that several stocks report negative book values of equity and the general approach in the Accounting and Finance literature is for such stocks to be considered as outliers and excluded from empirical samples[86]. These stocks are generally extreme value or extreme growth stocks and their exclusion might introduce bias in the analysis where MTB is an important variable (Brown et al. (2008)). Again, negative book value of equity might also arise when a stock has substantially underperformed in the past or when a stock has a very high level of leverage[87]. The exclusion of negative book value firms could introduce bias in the study as these factors (i.e., performance and leverage) underlie key hypotheses for target prediction. Given the importance of controlling for negative book values (as in prior research) and the possibility of generating new insights (e.g., by examining the relationship between negative book values and takeover likelihood), a negative book value dummy variable (NBVDummy) is added as a control variable to the model. This variable takes a value of one when book value of equity is negative and a value of 0, otherwise. Further, sensitivity analysis are conducted (by excluding negative BTM observations) to ensure that the results are not biased.

Although BTM is used as the primary measure of undervaluation in keeping with prior takeover prediction literature, it is worth reiterating that BTM is, perhaps, not the most suitable proxy for undervaluation. Other more suitable and advanced measures of undervaluation are discussed below. Nonetheless, these measures are not explored further in this study as testing the undervaluation hypothesis is not a main contribution of this

[86] Alternatively, such outliers are winsorised by replacing them with a new value.
[87] Shareholder equity generally measures how much shareholders will receive in the event that the firm is liquidated. The variable is easily obtained from the accounting equation as the difference between total assets and total liabilities (i.e., Total equity = total assets – total liabilities). As shown in equation 3.2.3 (2), studies (e.g., Powell (2001)) typically exclude intangibles from the computation of the variable, as the carrying value of intangibles (such as goodwill) is not, typically, realised when a firm is liquidated. Hence, total equity = total assets – total liabilities – total intangibles. Total equity can be negative when (other things remaining equal) the value of total assets declines (e.g., through a revaluation and write-off) or the proportion of total liabilities in the capital structure increases (e.g., through accumulated losses over several periods).

study. I therefore adopt the use of BTM as a measure of undervaluation in line with prior studies.

Indeed, Rhodes-Kropf et al. (2005) show that a firm's market to book (M/B) ratio in itself could be decomposed into a misvaluation component (M/V) and a growth component (V/B). That is,

$$M/B \equiv M/V \times V/B \ \ldots\ldots\ldots.. Eqn\ 3.2.3\ (4)$$

where M is the firm's market value, V is the firm's true value and B is the firm's book value. In log form, *Eqn 3.2.3 (4)* can be written as,

$$m - b \equiv (m - v) + (v - b) \ldots\ldots\ldots.. Eqn\ 3.2.3\ (5)$$

where lower case letters indicate logarithms of the different variables. $(m - v)$ represents misvaluation and should be zero if market participants have full knowledge of the firm's future cash flows, discount rates and growth opportunities. As suggested by Rhodes-Kropf et al. (2005) a deviation from zero can occur due to behavioural biases and/or information asymmetry between market participants and firms. In the current study, information asymmetry and the valuation problems it causes is treated as a main factor driving acquisitions (discussed in section 3.3.9). The challenge with using the Rhodes-Kropf et al. (2005) MTB decomposition model is determining the true value (V) of a firm. The researchers suggest various methods, perhaps, the most popular of which involves the use of book value, net income, the market leverage ratio and a vector of accounting information variables.

Ang and Chen (2006), Dong et al. (2006) and Bi and Gregory (2011) have also used the price to (residual income) value ratio as an alternative and, perhaps, a better measure of firm undervaluation (misvaluation or overvaluation). The model nonetheless requires the use of analyst forecast for firm earnings and dividends for a period of up to three years. As noted in Bi and Gregory (2011), UK analysts generally forecast up to two years ahead with data only really available for one-year forecasts. The researchers propose the estimation of two-year and three-year earnings and dividends forecasts by assuming that earnings and dividends grow at the rate of inflation plus 1.6% (representing the UK average real earnings growth rate). While this appears to be a more robust method for estimating the level of undervaluation, it is not adopted in this study. This is therefore a limitation of this study and an area in which it could be further improved.

Further, other measures of undervaluation including the earnings to price and dividends to price ratios have been used in some takeover prediction studies. For example, Palepu (1986) argues that a low PE ratio makes a firm an attractive takeover target as a bidder with a high PE ratio can scoop an 'instantaneous capital gain' by taking over such a target (p. 18). The underlying economic logic of this argument is questionable (also noted in Palepu (1986), p. 18). The attractiveness of low PE firms has been discussed in early studies such as Vance (1969), Mead (1969) and Tzoannos and Samuels (1972)). Vance (1969) contends that conglomerate predators are interested in firms with a low PE since a combination of a low PE ratio (of the target) and the high PE ratio (of the acquirer) significantly increase the acquirer's earnings per share. In line with Mead's (1969) merger profit hypothesis, this is thought to happen because the market tends to value the earnings of the combined firm at the higher PE of the bidder.

An alternative view is that a low PE proxies for growth opportunities – with low PE firms more likely to be undervalued. This view is consistent with the argument advanced by Mead (1969) and Vance (1969) as a bidder can increase its PE by unearthing the potential of the combined firm to grow future net cash flows due to the contributions of the 'cheaply' acquired target. There is, nonetheless, little empirical support for the discriminatory ability of PE in takeover prediction. Studies such as Powell (1997) and Powell (2001)) do not employ PE in their prediction models. Other studies (such as Palepu (1986), Ambrose and Megginson (1992), Barnes (1998), Espahbodi and Espahbodi (2003) and Ouzounis et al. (2009)) include PE as a discriminatory variable but find no empirical support for the hypothesis.

The lack of use of dividends (as a measure of performance, cash flow management or firm valuation) in many US based studies can be attributed to the finding that the number of firms paying dividends (especially in the US) has decline over time with a substantial proportion of listed firms paying no dividends (Fama and French (2002)). Studies employing a UK sample (e.g., Trajanowski and Renneboog (2005)) provide evidence that a majority of UK firms still pay dividends. Research on the role of dividends has shown that dividend plays a significant role in signalling. Bhattacharya (1979) and Miller and Rock (1985), for example, argue that dividend policy signals firm growth opportunities, financial viability and potential agency costs/problems when the level of information asymmetry between firms and their stakeholders is high.

The effect of dividend pay-out on takeover likelihood is, potentially, mixed. On the one hand, a high dividend pay-out (hence high dividend yield) signals management's desire to reduce free cash flow and hence, agency costs (Jensen and Meckling (1976) and Jensen (1986)). In line with Lintner (1956) and Kalay (1980), a high pay-out may signal that management envisages a growth in future earnings while a low pay-out may indicate low growth in future earnings. Conversely, the pecking order theory (Myers and Majluf (1984)) contends that a firm with low growth opportunities has no need to retain current earnings and is therefore more likely to increase its dividend pay-out.

There is little empirical evidence to support the use of dividend pay-out as a potential discriminatory variable for takeover prediction. Powell and Yawson (2007) and Espahbodi and Espahbodi (2003) find that targets, on average, have lower pay-out ratios and therefore lower yields. Contrary to the above findings, Brar et al. (2009) show that dividend yield and probability of takeover are positively correlated. The findings of Brar et al. (2009) provide some evidence that firms which are, potentially, undervalued – as measured by their dividend yield – are more likely to be takeover targets.

Besides the limited evidence to support their usefulness, the two variables (dividend yield and PE) tend to be highly correlated with the book to market ratio. I also find that several firms in my sample do not pay dividends in several periods. Given their high correlation with the BTM ratio, the empirical evidence supporting the use of BTM as a measure of misevaluation and the presence of non-dividend paying firms, neither dividend yield nor earnings to price is used as proxies for undervaluation in this study.

3.2.4 Industry disturbance hypothesis

This hypothesis stems from Gort's (1969) economic disturbance theory in which Gort explains how merger patterns vary across time and across industries. Gort (1969), Mitchell and Mulherin (1996) and Harford (2005) contend that merger waves result from shocks (including, economic, structural, technological and regulatory) to an industry's environment. The consolidation of a merger within an industry changes the competitive structure of that industry. Merging firms within an industry generally benefit from increased efficiency generated from internalised competition (Qiu and Zhou (2006)). This increased efficiency allows the merged firms to develop a competitive edge over rivals. Qiu and Zhou (2006) argue that mergers tend to cluster at industry level because a firm's incentive to merge (as a strategy to improve its capacity to compete) increases when other firms within the industry merge. The industry disturbance hypothesis therefore models the propensity for mergers to occur in certain industries based on past merger activity within the industry.

Palepu (1986) finds no support for the industry disturbance hypothesis. His results show that the occurrence of a takeover within an industry reduces the probability of future mergers occurring in that industry. Palepu (1986) does not advance any reasons for this observation. Antitrust avoidance and regulation can, perhaps, partly explain why a merger within an industry decreases the probability of further mergers occurring within that industry. Again, a takeover, potentially, reduces the number of 'suitable targets' in the industry, making it less likely for further takeovers to occur. If this is the case, then hypothesised relationship between takeover probability and industry disturbance will be reversed[88]. As specified in Palepu (1986), the industry disturbance hypothesis predicts that a merger within an industry stimulates further consolidation between firms in that industry. The hypothesis is stated as below.

> ***Hypothesis 3: Ceteris paribus, the likelihood of takeovers within an industry will increase with the announcement of a merger bid in that industry.***

In line with Palepu (1986) and Walter (1994), the industry disturbance dummy variable (IDummy) is used to model for industry disturbances. The variable takes a value of 1 if any merger is completed within a firm's industry (over the previous year) and a value of 0, otherwise. An industry is said to be 'disturbed' in year X1 (calendar year-end) if any merger is completed in this industry between 1 July X1 to 30 June X2. For example, an industry is considered disturbed in (calendar year-end) 2009 if a merger is completed in this industry between 1 July 2009 and 30 June 2010. This timing choice (i.e., 1 July X1 to 30 June X2) which is based on the June approach for portfolio formation is further discussed in chapter 4[89]. In many studies, industry is defined using the 4-digit SIC code system (Palepu (1986), Barnes, (1999), Brar et al. (2009), Ouzounis et al. (2009) and

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88 Some takeover prediction studies (including Ambrose and Megginson (1992), Powell (1997), Espahbodi and Espahbodi (2003), Brar et al. (2009)) do not use the industry disturbance hypothesis in their prediction models. The studies (including Ambrose and Megginson (1992), Powell (1997), Espahbodi and Espahbodi (2003), Brar et al. (2009)) which do not adopt the hypothesis do not discuss why the hypothesis is left out of their models. The hypothesis is adopted in the current study to ensure consistency with the Palepu (1986) study.

89 As will be fully discussed in section 4.2.5, M&A data for a period 1 July X2 to 30 June X3 is matched to accounting data for the year-ending X1 – the June approach.

Powell and Yawson (2011)). Some studies such as Walter (1994) have employed the 2 digit SIC code classification method. The definition and categorisation of industry groups in the thesis, which is based on the 4-digit SIC code classification, is fully discussed in chapter 4.

3.2.5 Free cash flow hypothesis

Free cash flow as defined by Jensen (1986) is 'Cash flow in excess of that required to fund all projects that have positive net present values (NPV) when discounted at the relevant cost of capital' (p. 323). Jensen (1988) advocates that all free cash flow must be returned to shareholders if the firm is to remain efficient. Nonetheless, returning this cash flow to shareholders reduces the resources available to managers (hence their power) and therefore subjects them to increased monitoring by capital markets when they seek new funds as the need arises (p. 12).

Excess free cash flow in a firm is likely to substantially increase the agency problem. As suggested by the agency theory, when in control of excess free cash flows, management is likely to engage in projects that do not enhance the wealth of shareholders. Jensen (1988), for example, contends that managers have incentives to use free cash flow to grow their firms beyond the threshold size for shareholder wealth maximisation. One reason for this is to create opportunities to reward middle management through promotion. In an active market for corporate control – one in which management teams compete for the rights to control shareholder resources and maximise shareholder wealth – management which hoards or misappropriates excess free cash flows are likely to face a challenge for corporate control (Manne (1965), Jensen (1986) and Powell (1997)). Besides the opportunity to correct management inefficiency, the bidding firm, in this case, is further attracted by the excess free cash flow in the target firm as this free cash flow can be used (by the bidder) to reduce the net cost of acquisition. The implication is that the availability of free cash flow is likely to increase a firm's takeover likelihood.

There is mixed empirical support for the hypothesis that excess free cash flow drives takeover activity. In support of the free cash flow hypothesis, studies (including, Powell (1997) and Espahbodi and Espahbodi (2003)) find that targets have comparatively higher levels of free cash flow when compared to bidders. Nonetheless, some studies (including, Powell and Yawson (2007), Brar et al. (2009)) do not find a significant difference between the levels of free cash flows in targets and non-targets. The latter studies find no strong support for the free cash flow hypothesis within their sample as their results show that free cash flow neither increases nor decreases takeover probability. To my knowledge, no study shows takeover probability to decrease with free cash flow.

As adopted in this study, the free cash flow hypothesis predicts that firms that have performed well enough to accumulate substantial free cash flows but have not returned such cash flows to investors are likely to become takeover targets (Jensen (1986) and Powell (2004)). The hypothesis can be stated as follows.

> ***Hypothesis 4: Ceteris paribus, takeover likelihood increases with a firm's level of free cash flow.***

Consistent with Powell and Yawson (2007), free cash flow is defined as the ratio of net cash flow from operating activities [wc04860][90] less capital expenditures [wc04601] scaled by total asset [wc02999][91]. As in Powell and Yawson (2007), all three variables are drawn from year-end financial statements within the same period. The net cash flow from operating activities represents operating income before depreciation, adjusted for interest expense, taxes and dividends. Hence, this proxy considers free cash flow as the residual cash flow after all major required expenditures (operating expenses, finance interest and taxes) and investments. The limitation of the measure is that it does not consider whether the investments (capital expenditures) are directed towards shareholder wealth maximising projects.

3.2.6 Growth-resource mismatch hypothesis

The neo-classical view of mergers holds that mergers are perpetrated to create value through synergies (see, Manne (1965) and Trautwein (1990)). Merging firms can also create synergies in operations through economies of scale and scope, the elimination of redundancies and the optimisation in the use of equipment, facilities and resources. Managerial synergies, for example, can be achieved when the bidder has superior management capability (in, for example, planning, controlling, or monitoring) which can improve the target's operations. Managerial synergies can also be achieved if the target management is underperforming such that new management (bidder) can better utilise the

[90] DataStream defines net cash flow from operations as the difference between cash inflow and outflow due to a firm's operations.
[91] The net cash flow from operating activities represents operating income before depreciation, adjusted for interest expense, taxes and dividends.

resources and opportunities available to the target to provide increased benefits to the shareholders (Trautwein (1990)).

Devos et al. (2009), for example, investigate the sources of gains in mergers in relation to three key aspects: financial synergies, operational synergies and market power. They find that the average value of synergies created is equivalent to 10.03% of the combined pre-merger equity value of the two firms[92]. Interestingly, Devos et al. (2009) show that over 81% of all synergies created from mergers are in terms of operational synergies, with financial synergies making up just about 17% of total synergies.

The growth-resource mismatch hypothesis builds on the neoclassical motive of takeovers – to generate synergies through complementarities (Manne (1965), Palepu (1986) and Trautwein (1990)). It asserts that M&A is pursued by resource-rich or resource-poor bidders looking for strategic partners (resource-poor or resource-rich targets, respectively) to complement. For example, resource-rich bidders with low growth opportunities generate growth opportunities by acquiring resource-poor targets with high growth opportunities. Such an alliance creates synergies as the bidder's excess resources are used to pursue the target's growth opportunities.

The growth-resource mismatch hypothesis contends that two variables – the level of firm growth and the amount of resources available to the firm – can combine to moderate the attractiveness of the firm as an acquisition target. Palepu (1986) proposes that low-growth-resource-rich firms as well as high-growth-resource-poor firms will make attractive targets. Palepu (1986) defines a low-growth-resource-rich firm as one which has sustained low levels of growth in sales, yet is rich in liquid resources and has a low gearing ratio. He defines a high-growth-resource-poor firm as a firm which has maintained high growth in sales despite its low liquidity and high leverage position. A firm with high liquidity and low leverage (i.e., resource-rich firm) should intuitively be matched with growth in sales (i.e., growth opportunities). If this is not the case (i.e., a mismatch exists), then an opportunity arises for a bidder to create synergies by correcting this mismatch.

[92] Other studies (including Houston et al. (2001) and Bhagat et al. (2005)) have reported the creation of synergies of about 13% (on average) of the pre-merger value of the two firms. Evidence from the event study literature (e.g., Bradley et al. (1988) and Becher (2000)) confirms that the combined firm earns positive abnormal returns around the merger period.

While this hypothesis is, perhaps, theoretically sound, there is little empirical evidence to support its validity and usefulness in takeover target prediction. In support, Palepu (1986) finds evidence that takeover likelihood increases with a mismatch between growth opportunities and firm resources. Espahbodi and Espahbodi (2003) find that targets have a higher mismatch between growth and resources when compared to non-targets[93]. In line with Palepu (1986), the hypothesis is stated below.

Hypothesis 5: Ceteris paribus, low-growth-resource-rich firms as well as high-growth-resource-poor firms are more likely to become takeover targets.

Palepu (1986) employs a growth-resource mismatch dummy variable (GRDummy) to proxy this hypothesis. The Palepu (1986) approach is replicated in this study. The GRDummy is computed from three variables: sales growth (percentage increase in net sales [wc01001]), liquidity (cash and short term investments [wc02001] to total assets ratio [wc02999]) and leverage (debt [wc03255] to equity [wc03995] ratio). A mismatch between growth opportunities and resources is said to occur when (1) a firm has high sales growth accompanies by low liquidity and high leverage, or when (2) a firm has low sales growth accompanied by high liquidity and low leverage[94]. As in Palepu (1986), these variables are characterised as low or high by comparing them with the industry average[95]. High indicates that the value is higher than the industry mean, and vice versa. The GRDummy takes a value of 1 in these two cases ((1) and (2) above) and a value of 0 in all other combinations of growth, liquidity and leverage.

Ideally, a forecast of the firm's future growth level should be used in measuring growth opportunities, but since this information is not readily available (or might be unreliable), future growth potential is estimated from past growth levels. Palepu (1986) uses the three-year average historical sales growth as a proxy for the firm's future growth levels. This method assumes that a firm's current growth level is the best indicator of its future growth potential. This approach is standard in the literature (Barnes (1999), Brar et al. (2009), Ouzounis et al. (2009)). Nonetheless, the current study employs a panel type data structure

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[93] Espahbodi and Espahbodi (2003) later dropped the growth-resource mismatch hypothesis from their model as the difference between targets and non-targets (in terms of the level of mismatch) was not statistically significant.

[94] Leverage models for the firm's interest obligations. High leverage implies that the firm will have lower available cash resources after it meets its yearly debt obligations. A combination of high liquidity and low leverage indicates overall high resource availability while a combination of low liquidity and high leverage indicates overall low resource availability.

[95] Industry classifications are discussed in chapter 4.

with different firm-years being considered as independent events (this is further discussed in section 4.2). Growth opportunities are therefore measured by using the sales growth level in the previous year. A firm's sales growth in year t is computed from annual sales or revenues [wc01001] as follows:

$$SalesGrowth_t = \frac{Sales_t - Sales_{t-1}}{Sales_{t-1}} \dots \dots \dots Eqn\ 3.2.6\ (1)$$

Resource availability is measured as a function of both a firm's level of liquidity and its level of leverage (Palepu, 1986). Liquidity measures the level or proportion of liquid assets (cash and near cash items) within a firm's asset structure. This measure of liquidity has been applied by Palepu (1986) and Loderer et al. (2011). Consistent with these studies, liquidity is defined as the ratio of cash, short-term investments and near cash items [wc02001] to the firm's total assets [wc02999]. In line with Palepu (1986), leverage is measured as the ratio of total debt [wc03255] to total equity [wc03995]. The rationale of using leverage to determine resource availability is due to the fact that highly levered firms have higher interest and repayment commitments which act as a constraint on the firm's liquid resources. Therefore, a high level of liquid assets and a low leverage (implying high resource availability), will allow a firm to engage in new projects while low liquidity and high leverage (implying low resource availability) will constrain a firm from investing in new projects[96].

3.2.7 Tangible assets hypothesis

The importance of asset structure on financial decision making and policy within the firm have long been studied in the literature (see, for example, Myers (1977), Myers and Majluf (1984), Ambrose and Megginson (1992)). Assets are said to provide financial slack for a firm, enabling it to raise debt capital rather than turn to the stock market in times of need (Myers and Majluf (1984)). Stulz and Johnson (1985) and Ambrose and Megginson (1992) contend that the level of tangible fixed assets (property, plant and equipment) within a firm can proxy its debt capacity. All things being equal, a firm with tangible assets – a high proportion of tangible fixed assets in its asset portfolio (i.e., high debt capacity) – is likely to be a more attractive takeover target. This is because the tangible assets can be used as collateral security by a prospective bidder to raise some of the funds needed to finance the proposed takeover. The presence of tangible assets or tangible fixed assets within a firm's

[96] This is also based on the potential restrictions that debt holders place on firms through debt covenants coupled with the fact that interest to debt must be paid before the firm can engage in any new investment opportunities.

portfolio makes it an attractive target by reducing its implicit takeover cost to the bidder[97]. Further, asset tangibility is, perhaps, important for firm valuation, especially when the level of information asymmetry between the target and the bidder is high. Non-tangible assets such as brands, patents, R&D and goodwill are, arguably, difficult to value. In line with the asymmetric valuation hypothesis (section 3.3.9), the ease of valuing firms with tangible assets can improve their attractiveness as takeover targets. The 'ease of valuation' perspective of tangible assets hypothesis is not fully consistent with the undervaluation hypothesis. This is because a firm with more tangible assets is less likely to be undervalued by the market. Hence, as suggested by the undervaluation hypothesis, such a firm should have a low takeover probability.

There has been some empirical evidence to support the tangible assets hypothesis, with researchers (including Ambrose and Megginson (1992), Powell (1997), and Espahbodi and Espahbodi (2003)) finding that takeover probability increases with the proportion of tangible assets in a firm's total asset portfolio. The hypothesis – first employed in takeover prediction by Ambrose and Megginson (1992) – predicts that firms with substantial tangible assets (such as plant and machinery) in their total asset portfolio are more attractive targets to bidders. The hypothesis can be stated as below.

> ***Hypothesis 6: Ceteris paribus, takeover probability increases with the proportion of tangible assets in a firm's total asset portfolio.***

The reported value for property, plant and equipment net of reserves is used as a measure of the firm's level of tangible fixed assets[98]. In line with prior studies (such as Powell (1997) and Ambrose and Megginson (1992)), tangible assets is proxied by the ratio of tangible fixed assets or property, plant and equipment [wc02501] to total assets [wc02999].

3.2.8 Firm size hypothesis

Palepu (1986) argues that takeover probability is decreasing in firm size, with small firms highly susceptible to takeover bids. Palepu (1986) contends that several size-related transaction costs[99] are associated with acquiring a target and, therefore, the number of

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[97] In line with this, Eddey (1991) proposes the raider theory of takeovers – that bidders (or 'raiders') interested in 'buying and striping' firms will be attracted to firms with a high proportion of tangible fixed assets in their asset structure.

[98]Net property plant and equipment (PPE) represents the gross value of PPE less accumulated reserves for depreciation, depletion and amortization (DataStream definition).

[99] These costs can include the market price plus premium for the target, M&A negotiation fees (adviser, consultants and investment banks, amongst others), the cost of fighting any target

viable bidders for a target decreases as its size increases. This perspective is supported by Gorton et al. (2009) who contend that bidding firms can only, generally, acquire comparatively smaller target firms. Palepu (1986) and Gorton et al. (2009) discuss the effect of target firm size with reference and comparison to the characteristics of the bidder by positing that 'comparatively smaller' firms are suitable targets as they are likely to be more affordable for a 'comparatively larger' bidder. In general, such a reference to the bidder's characteristics introduces a look-ahead bias as the characteristics of the bidder are unknown *a priori* and hence cannot be added to the model. The norm is to compare a target against the population of non-targets. Palepu's 'affordability' argument (proxied by firm size) is, perhaps, justified only if takeover probably of a firm (e.g., firm i) increases with the number of firms, γ, which are larger than firm i. If this is the case, a better (or unbiased) proxy for affordability might be γ rather than the size of firm i[100].

Some studies (including Hasbrouck (1985), Bartley and Boardman (1990) and Walter (1994)) employing the contentious non-random (matched or unmatched) sampling methodology similar to that employed in the Palepu (1986) study, concur with Palepu's finding that targets are generally smaller in size. This finding is not, however, supported across the literature (see, for example, Ambrose and Megginson (1992) and Powell (1997)). Powell (1997), for example, finds that the purported negative relationship between size and takeover probability is not robust across time. Using a multinomial model (distinguishing between hostile targets, friendly targets and non-targets), Powell (1997) also shows that the relationship between size and takeover probability is negative for friendly targets but consistently positive for hostile targets. The hypothesised negative relationship between firm size and takeover probability is further disputed by studies from the merger wave literature which argue that some waves (such as the 1980s wave) are characterised by the acquisition of larger targets as bidders view growth, capacity development and economies of scale as a key merger motive (Hughes (1989), Mitchell and Mulherin (1996) and Harford (2005)).

resistance and the cost of absorbing the target into the bidder's operating framework (see Palepu (1986) and Powell (2001) for a discussion).

[100] The number of firms of size larger than the size of firm i, is a better proxy for affordability of firm i, as the proxy generates a linear pattern across the population with the smallest firm having the largest γ, and vice versa. γ can be made more analytically tractable by taking its inverse or natural log.

Again, the 'matching criteria and state-based sampling methodology'[101] employed by Palepu (1986), Hasbrouck (1985), Powell (1997), Barnes (1990), Barnes (1998), Powell (2001), and Brar et al. (2009), potentially, explains why the relationship between size and takeover probability might have been mis-specified (although supported) in some prior empirical studies (Shumway (2001)). Further, some researchers (e.g., Brar et al. (2009)) constrain their samples through the imposition of a minimum size criterion for firm inclusion in the sample. This constraint masks the relationship between firm size and takeover probability through the elimination of small firms. The current study contributes to the literature by redeveloping the firm size hypothesis as discussed in section 3.3.2. As in Palepu (1986), the (old) firm size hypothesis is stated as below.

Hypothesis 7: Ceteris paribus, takeover probability decreases with firm size.

Several measures of firm size have been employed in the literature. These include: net book assets, market capitalisation, sales, capital stock and total assets, amongst others (see Palepu (1986), Brar et al. (2009) and Barnes (2000)). The natural log of these variables is used as it improves the analytical tractability of the variable. In the current study, firm size is proxied by the log of total assets (consistent with Powell (1997), Powell and Yawson (2007), Cornett et al. (2011) and De and Jindra (2012))[102]. The total asset proxy captures all the different size related transaction costs noted above. Palepu (1986) and Ambrose and Megginson (1992) use the net book value (i.e., total assets less total liabilities) as a measure of target firm size. While the net book value can, perhaps, proxy for the direct cost of acquisition (or purchase price), it is unlikely to proxy for other related transaction costs such as the cost of absorbing the target into the bidder's operating framework[103].

3.2.9 Firm age hypothesis

Substantial research has been done in the firm life cycle literature which focuses on understanding the different stages in the life cycle of a typical firm (including industry entry, growth, decline and exit). This literature frequently attributes firm survival (age) to the ability of firms to learn actively or passively over time (Hopenhayn (1992), Pakes and Ericson (1998) and Bhattacharjee et al. (2009)). In line with the learning perspective, Bhattacharjee et al. (2009) contend that exit rates (due to the hazard of takeovers or

[101] This methodology is further discussed in section 2.6.3.
[102] The natural log is used in order to improve scaling and hence analytical tractability.
[103] This is because a firm can have substantial total assets but a low net book value due to high long term debt in its capital structure. The net book value of this firm will be equivalent to that of a small firm with low debt. While both firms will have the same net book values, it is unlikely that both firms will have the same probability of receiving a bid, other things being equal.

bankruptcies) should decrease with age. Firm age is highlighted in Brar et al. (2009) as a potential discriminatory variable between targets and non-targets. Nonetheless, Brar et al. (2009) neither present any theoretical justification to support the hypothesis, nor conduct any related empirical tests[104]. Bhattacharjee et al. (2009) also employ firm age as a predictor of business exit due to the hazard of takeovers or bankruptcy. Bhattacharjee et al. (2009) find evidence of a negative relationship between age and firm exit. For consistency, the hypothesis is included in this section (section 3.3) given that it was highlighted in a prior takeover prediction study. Brar et al. (2009) indicate that takeover probability is expected to have a negative relationship with firm age. This hypothesis is redeveloped in the current study and a theoretical justification of the expected relationship between age and takeover probability is further discussed in section 3.3.5. The (old) firm age hypothesis (as implied in Brar et al. (2009)) is stated below.

Hypothesis 8: Ceteris paribus, takeover probability decreases with firm age.

Two measures of age have been used in the finance literature: number of years since listing (IPO) and number of years since firm incorporation (see, for example, Loderer et al. (2011) and Shumway (2001)). Loderer et al. (2011) find that incorporation age and listing age for a sample of US firms are highly correlated with a correlation coefficient of 0.668 and can therefore be used interchangeably. Studies on business exit (such as Bhattacharjee et al. (2009) and Loderer and Waelchli (2010)) generally use listing age (i.e., the difference between the current year and the year in which the firm was listed). However, these studies focus the life cycle concept with a firm’s IPO considered to be the starting point. In the current study, the focus is on how a firm’s characteristics (such as productivity of its assets and ability to innovate) changes with age hence affecting its likelihood of takeover. In this study, firm age is measured as the number of years since firm incorporation [wc18273] – the incorporation age – i.e., the time span (in years) from incorporation to the current year.

3.2.10 Summary

Eight old takeover prediction hypotheses have been discussed in this section. Two of these old hypotheses (firm size and firm age) are redeveloped in this study to generate new insights as discussed in section 3.3.2 (firm size) and 3.3.5 (firm age) below. As discussed in chapter 2 (see section 2.6.5), these eight hypotheses (hypothesis 1 – hypothesis 8) have been recurrently used in the takeover target prediction modelling literature. The empirical

[104] The firm age variable is dropped from their analysis at an early stage (prior to their univariate analysis).

evidence on their validity is mixed. This study makes a contribution to the literature by introducing eleven new takeover prediction hypotheses (hypothesis 9 – hypothesis 19), which when combined with the six old hypotheses (hypothesis 1 – hypothesis 6), improves the theoretical and empirical framework for predicting future takeover targets. The eleven new hypotheses are discussed in section 3.3.

3.3 New hypotheses for takeover target prediction

3.3.1 Overview

The phrase ‘new hypotheses’ is used in this study because, to my knowledge, this is the first time that these hypotheses are applied in the prediction of takeover targets. As will be discussed, some of the hypotheses are developed from empirical research in other areas of finance and most of the hypotheses build on established theories. Some new hypotheses, such as firm size, capital structure and firm lifecycle, constitute an expansion of old takeover prediction hypotheses.

This section discusses the new hypotheses for takeover prediction developed in this study. One key hypothesis used in prior studies is the firm size hypothesis, which argues that takeover probability is decreasing in firm size. An alternative view is adopted in this study (i.e., the hypothesis is redeveloped in this study). Also, firm age is briefly highlighted as a potential moderator of firm takeover probability in Brar et al. (2009). Nonetheless, Brar et al. (2009) do not use firm age when developing their model. This hypothesis is included under new hypotheses as it is also redeveloped in this study. The eleven new hypotheses discussed in sections 3.3.2 to 3.3.13 include: firm size, firm age, capital structure, M&A rumour, payroll synergies, share repurchases, financial distress, asymmetric valuation, barriers to entry, market liquidity and market economics hypotheses.

3.3.2 Firm size (new) hypothesis

The relationship between firm size and takeover probability is, perhaps, not linear previously considered. As discussed in section 3.3.8, the use of firm size as a proxy for the ease of affordability might introduce look-ahead bias in prediction studies given that the characteristics of the bidder are not known *a priori*. Even if firm size measures affordability (as in Palepu (1986)), the use of net book value of assets as a measure of firm size (in studies such as Palepu (1985), Ambrose and Megginson (1992) and Espahbodi and Espahbodi (2003)) as opposed to market value (for example) fails to fully capture the concept of affordability as discussed in section 3.3.8. Arguably, the ‘old’ firm size hypothesis (Palepu (1986)) is mainly consistent with an antitrust avoidance rationale and a variable cost minimisation motive for target selection[105].

As will be discussed here, when other theories/motives of takeovers (such as economies of scale, managerial hubris, managerial utility maximisation, empire-building, information asymmetry, and transaction costs) are taken into consideration, this view is not supported. In fact, it is likely that ‘mid-sized’ firms will face a higher takeover threat in comparison to their small and large counterparts. While the smallest firms are the easiest to acquire (due to low capital requirement), their acquisition is unlikely to allow managers to attain most of the aforementioned acquisition motives. If ‘bigger is better’ to bidding management[106], and it is assumed that Gibrat’s Law[107] (on firm size distribution) holds, then a firm’s takeover likelihood should generally increase with size – at least for firms below the mean (or median) firm size. Notwithstanding, high transaction costs and the limited number of larger firms (γ) can play an important role in shielding the largest firms in the industry from takeover threats[108].

The ‘new’ firm size hypothesis argues that the relationship between firm size and takeover probability is essentially nonlinear, with the smallest and largest firms facing the least takeover threat. Other theories of takeovers e.g., the managerial (utility) theory and the empire building hypothesis, support this hypothesised relationship.

Managerial (utility) theory of mergers stipulates that managers engage in merger activity to attain increased managerial utility (see Mueller (1969) and Marris (1963)). Clearly, managers are unlikely to consistently pursue mergers only with the aim of maximising their own utility without any regard for (or at the detriment of) their shareholders. Jensen and Meckling’s (1976) argument – that managers are more likely to adopt shareholder

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105 That is, bidding firms show preference for smaller targets because such mergers are likely to face little scrutiny from antitrust regulators (antitrust avoidance) and because the cash outlay to target shareholders is low (variable cost minimisation).

106 As predicted by theories such as economies of scale and scope, managerial hubris, managerial utility maximisation, empire-building, information asymmetry, and transaction costs. This will be discussed further.

107 Gibrat’s Law proposes that firm size is log normally distributed (see Angelini and Generale (2008) for evidence on firm size distribution). That is, the log of firm size of all firms in the population follows a normal distribution.

108 As in section 3.3.8, γ is used to denote the number of firms of size larger than a potential target. It is assumed that a firm (potential target) mainly faces a takeover threat from the γ (viable bidders) population. In line with Gibrat’s Law, γ declines as (log) firm size increases.

wealth *satisficing* objectives than shareholder wealth *maximising* objectives – provides a more plausible justification of the managerial utility theory. Managers adopting a shareholder wealth *satisficing* objective will, perhaps, engage in mergers that do not adversely impact on the wealth of their shareholders but allows them to increase their own utility. Consistent with the managerial theory, prior empirical evidence suggests that bidders do not gain from takeovers and may even earn negative abnormal returns from takeover activity[109]. This suggests that, on average, bidders pursue their self-interests through mergers (Malatesta (1983)). The empire-building hypothesis (Marris (1963)) proposes that managers engage in mergers to increase firm size, and with it, salary, power and social status. The finding that managers systematically overpay for targets – the hubris hypothesis (see Roll (1986) and Hayward and Hambrick (1997)) – further supports a managerial self-interest motive of mergers. A related argument for the consummation of mergers is advanced by the monopoly theory. This theory argues that mergers are consummated by firms aiming to gain market power (e.g., Eckbo (1992)). The theory suggests that gains in mergers arise from the reduction in industry competition, permitting an increase in prices and thus a general increase in industry profits.

To facilitate further discussion, the (new) firm size hypothesis can be broken down into two segments – A and B. Segment A predicts that takeover probability will increase with firm size for firms in the population with firm size below a threshold[110]. Segment B of the hypothesis predicts that takeover probability will decline with firm size for firms in the population with firm size above a threshold.

The main argument for the relationship in segment A (takeover probability increases with firm size) is that the acquisition of smaller targets is less likely to allow prospective bidders to attain either neoclassical or managerial utility motives of takeovers. While bidding firms are likely to pursue targets that are comparatively smaller in size for transaction costs reasons (Palepu (1996), Ambrose and Megginson (1992), Powell (1997) and Gorton et al. (2009)), the creation of value by the bidder (through increased synergies and economies of scale) is, potentially, dependent on the size of the target. Gorton et al. (2009), for example, contend that mergers with larger targets are more attractive because of the potential to

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[109] See, for example, Malatesta (1983), Jensen and Ruback (1983), Franks and Harris (1989), Holl and Kyriazis (1997), Higson and Elliot (1998), Gregory (1997), Kennedy and Limmack (1996), Limmack (1991) and Sudarsanam and Mahate (2003).

[110] If the distribution of firm size is log normal (Gibrat's law), then this threshold can be approximated by the median or mean firm size.

generate higher value due to larger economies of scale. Similarly, bidders seeking to generate monopoly power or benefit from the acquisition of undervalued firms are more likely to achieve such motives through the acquisition of the largest of their potential targets. Likewise, bidders with an empire-building motive or bidders whose decision to acquire is driven by hubris, are, perhaps, more fulfilled by acquiring the largest firm in their list of potential targets.

In segment A (i.e., below a size threshold), there are, perhaps, transaction cost savings to be made by acquiring larger rather than smaller firms. Prior studies (such as Palepu (1986) and Gorton et al. (2009)) implicitly assume that the fixed costs of takeovers (costs which are unrelated to target size) are insignificant and only variable costs of takeovers (e.g., offer price) really matter. There is evidence that these fixed costs are quite substantial, particularly when the value of acquisition is low. This is because the fees paid to advisors in M&A transactions – which are usually a proportion of the value of the transaction – decline with the transaction value (Kosnik and Shapiro (1997)). Using a US sample of 5,337 deals between 1995 and 2000, Hunter and Jagtiani (2003), for example, provide some empirical evidence to show that the fee paid by targets decreases as the value of the transaction increases. This is in line with popular fee structuring formulae such as the Lehman and Double Lehman fee structure used by many investment banks (Kosnik and Shapiro (1997)). This stepped fee structure (which generates a higher fee to value ratio for small takeovers) imposes significant fixed costs in the acquisition of smaller firms. Bidders might thus benefit from economies of scale in transaction costs by acquiring the largest of their potential targets. Further, the evidence suggests that M&A advisors are likely to recommend larger rather than smaller firms as potential targets for both reputational and financial purposes. The empirical evidence suggests that the reputation of M&A advisors (e.g., their position on M&A league tables), as well as, their revenues is generally tied to the value of deals in their portfolio (see, for example, Plaksen (2011) and Walter et al. (2008)).

The problem of information asymmetry and its effect on the market mechanism – the market for lemons – has been discussed in prior research (Akerlof (1970)). The market for firms is, perhaps, not an exception to this problem. Some researchers (e.g., Pettit and Singer (1985)) argue that, due to a lack of economies of scale in information production and distribution, smaller firms are inclined to produce and distribute less information about themselves, thus leading to a higher level of asymmetry between them and their stakeholders. This problem of comparatively higher information asymmetry in smaller firms is further exacerbated by the lack of significant analyst following. Eleswarapu et al. (2004), for example, show that a group of small US firms (with an average market capitalisation of $106 million) had no (0) analyst coverage. Eleswarapu et al. (2004) also find that analyst following increases with firm size, with up to 35 analysts following large firms (with an average market capitalisation of $62.6 billion). This suggests that, if bidders are cautious of purchasing 'lemons', they are likely to bid for low information asymmetry firms – which produce and distribute large volumes of information about themselves and are followed by several analysts. The implication is that bidders will be, perhaps, more inclined to acquire larger than smaller targets on average.

Segment B of the hypothesis argues that takeover likelihood declines with firm size beyond a size threshold. This part of the hypothesis is consistent with the old firm size hypothesis discussed in prior studies (see, for example, Palepu (1986), Hasbrouck (1985), Bartley and Boardman (1990), Walter (1994), Powell (2001), amongst others). These prior studies argue that there is a linear relationship between firm size and takeover likelihood with large firms being least susceptible to takeovers. As noted by Gorton et al. (2009), this might be the case because a larger acquisition is more difficult to finance or because it is more difficult (and more risky) to raise new debt capital to fund larger acquisitions. Further, use of equity to finance acquisitions will lead to dilution of ownership (with the effect increasing in target size) and a loss of control for incumbent management (Gorton et al. (2009)).

The arguments put forward by Gorton et al. (2009) and Palepu (1986) combines with Gibrat's law on the distribution of firm sizes in the population to, possibly, explain why the resource requirements (transaction costs and cost of reorganisation) involved in the acquisition of larger targets limits the number of viable bidders. If Gibrat's law holds, the number of viable bidders (γ) in the population will decrease with (the log of) firm size for all firms larger than the median firm[111]. The implication is that the takeover risk faced by comparatively larger firms (firms with size above the median) will continuously decline as size increases. All things being equal, the largest firms in the population will, perhaps, face little or no risk of takeover. Overall, Segment A and segment B generate an inverse U-shaped relationship between firm size and takeover probability.

[111] This assumes that a viable bidder is any firm with (log) size greater than the (log) size of the target.

As discussed above, the old firm size hypothesis is, perhaps, mainly consistent with an antitrust avoidance motive and a variable cost minimisation motive of takeovers. These two motives do not appear to be strong enough to fully explain the relationship between firm size and takeover likelihood. Further, there is lack of robust empirical evidence to support the old firm size hypothesis. The new firm size hypothesis is more consistent with both the neoclassical and managerial motives of takeovers. It is also consistent with other factors (such as transaction costs, role of advisers, and information asymmetry considerations) which, arguably, play a role in moderating the choice of takeover targets. This hypothesis of an inverted U-shaped relationship between firm size and takeover likelihood has not been tested in the literature to the best of my knowledge. The hypothesis is stated below.

> ***Hypothesis 9: Ceteris paribus, takeover probability is an inverted U-shaped function of firm size. Takeover likelihood initially increases with size then declines as firm size exceeds a threshold.***

As discussed in section 3.2.8, firm size is proxied by the natural log of total assets [wc02999]. The nonlinear relationship is captured by adding a squared term (the natural log of total assets squared) to the model. It is expected that if the hypothesis holds, then takeover probability will be positively related to firm size (log total assets) and negatively related to firm size squared (log total assets squared).

3.3.3 Firm capital structure hypothesis

Although leverage has been used as a control variable in almost every takeover prediction model, its hypothesised relationship with takeover probability is hardly discussed. Palepu (1986) uses firm leverage together with growth and liquidity to develop a proxy for the growth-resource mismatch hypothesis. Palepu (1986) also includes leverage as an independent variable in the model noting that the relationship between leverage and takeover probability cannot be hypothesised *a priori*. In his empirical analysis, Palepu (1986) finds a negative relationship between leverage and takeover probability.

The role of target financial slack (as discussed in Myers and Majluf (1984), Smith and Kim (1994) and Morellec and Zhdanov (2008)) and deterrent effects of high leverage (as discussed in Harris and Raviv (1988), Stulz (1988), Safieddine and Titman (1999), Garvey and Hanka (1999) and Billet and Xue (2007)) can, perhaps, explain why leverage and takeover probability can be negatively related. Firms with low debt in their capital structure offer a bidder more financial slack (i.e., the ability to borrow capital, if needed). The total available financial slack decreases as the target's level of leverage increases. Acquiring a highly levered target imposes new risk on the bidder as the bidder inherits the target's debt interest commitments. Both factors (financial slack and risk of high leverage) result in a negative relationship between leverage and takeover probability.

This theoretical argument is, however, not fully supported by the empirical evidence. Several studies adopting Palepu's prediction model (hypothesis and variables) find mixed results. Some studies (such as Hasbrouck (1985), Espahbodi and Espahbodi (2003) and Bhanot et al. (2010)) find that, on average, targets have higher (but statistically indifferent) leverage level when compared to non-targets. Other studies (such as Ambrose and Megginson (1992), Powell (1997), Powell (2004), Barnes (1998) and Barnes (1999)) show that there is a significant positive relationship between leverage and takeover probability. The aforementioned studies neither corroborate Palepu's finding nor the theoretical arguments (i.e., financial slack and risk of high leverage) for a negative relationship between leverage and takeover probability. These mixed results motivate a closer look at the relationship between firm leverage and takeover probability.

The firm capital structure hypothesis introduced in this study predicts that, below a certain threshold, the relationship between takeover probability and firm leverage is direct but the direct relationship reverts as leverage increases further. This implies an inverted U-shaped relationship between leverage and takeover probability. For discussion purposes, this hypothesis is broken down into 2 segments – segments A and B. Segment A predicts that takeover probability will increase with leverage up until a leverage threshold. Segment B of the hypothesis predicts that takeover probability will decline with leverage beyond the leverage threshold. The rationale for this prediction is discussed further below.

Classic capital structure theory (Modigliani and Miller (1958) and Modigliani and Miller (1963)) as well as the trade-off theory of firm financing behaviour (Myers (1984)) fail to explain why a significant proportion of firms (even successful firms with presumably low bankruptcy risk) have very little debt in their capital structure (see, for example, Fama and French (2002), Frank and Goyal (2003), Leary and Roberts (2010) and Halov and Heider (2004), amongst others). The pecking order theory (Myers (1984) and Myers and Majluf (1984)) suggests that, due to agency conflicts and tax reasons, managers will only take on additional external financing (debt and new equity issues) when they are unable to generate funds internally. Shyam-Sunder and Myers (1999), for example, provide some empirical evidence to support the pecking order theory of corporate financing behaviour. The theory has, however, been criticised for not fully explaining a majority of corporate financing decisions, particularly the finding that many firms turn to issue equity in preference to debt (Helwege and Liang (1996), Fama and French (2002), Frank and Goyal (2003), Leary and Roberts (2010), Halov and Heider (2004) and Fama and French (2005)). Several studies which find no support for the pecking order theory (including Fama and French (2002), Halov and Heider (2004), Frank and Goyal (2003)) find that the preference for equity over debt as a source of external financing, is especially common in well-performing high-growth firms. This exception in high growth firms is also noted in studies (such as Lemmon and Zender (2010)) which find support for the pecking order theory.

Based on this evidence, it appears that well-performing high-growth firms are likely to follow a unique pecking order with a preference for internal financing (retained earnings), then equity (when internally generated funds are depleted) and finally debt (when all other sources of funds are exhausted). The reasons for this unique pecking order include issues of information asymmetry (Frank and Goyal (2003)), adverse selection (Halov and Heider (2004)) and debt capacity restrictions (Lemmon and Zender (2010)). This unique pecking order followed by 'well-performing high-growth' firms corroborates much of the empirical evidence on firm financing choices (see Helwege and Liang (1996), Fama and French (2002), Frank and Goyal (2003), Leary and Roberts (2010), Halov and Heider (2004), Fama and French (2005), and Lemmon and Zender (2010)). For the purpose of takeover prediction, leveraging can therefore be considered as a characteristic of firms which are less able to generate and retain sufficient funds to meet reinvestment needs. In line with the empirical findings discussed above, leveraging can also be considered a characteristic of firms which are unlikely to be 'well-performing high-growth' firms. These firms therefore tend to issue debt to fund their financing deficit. As the problem becomes more severe, the financing deficit increases and more debt is issued. The implication is that, all things being equal, leveraging is a sign that firms are either facing financing difficulties or lack sufficient financial slack to meet investment needs.

This argument is directly supported by theoretical and empirical evidence (e.g., Israel (1992)) which predicts that more efficient firms are likely to issue less debt. Further, evidence from the bankruptcy prediction literature (see, for example, Altman et al. (1977), Taffler (1983, 1984), Shumway (2001) and Agarwal and Taffler (2007), amongst others) overwhelmingly shows that high leverage is synonymous to financial distress, insolvency and corporate bankruptcy – key indicators of managerial inefficiency. It can be expected, consistent with the management inefficiency hypothesis, that firms with high leverage might constitute attractive targets, especially to resource rich firms. Contrary to Palepu's (1986) finding, but consistent with much of the empirical evidence (Hasbrouck (1985), Bhanot et al. (2010), Ambrose and Megginson (1992), Powell (1997), Barnes (1998, 1999), Espahbodi and Espahbodi (2003) and Powell (2004)), this implies a direct relationship between leverage and takeover probability. For discussion purposes, this is referred to as segment A of the relationship between takeover likelihood and firm leverage.

I argue that there is a discontinuity in this relationship when leverage becomes 'too' high (segment B). At high debt levels (above a threshold), the firm, possibly, no longer becomes an attractive target. There are two main reasons for this postulation. First, firms with high levels of debt (presumably above the threshold) face increased monitoring from debt holders. Jensen (1986) argues that high debt levels result in low free cash flows and hence low agency problems. A high debt level also proxies for high managerial commitment to shareholders and therefore low opportunity for improvements by a prospective bidding firm (Jensen (1986)). Supporting evidence provided by Safieddine and Titman (1999) suggests that higher leverage helps firms remain independent, not because it entrenches managers, but because it commits managers to making the improvements that would be made by potential raiders. This implies the attractiveness of a firm as a target, potentially, declines as leverage goes beyond a certain threshold.

The second reason for an inverse relationship between leverage and takeover probability is the role of leverage as a takeover defence mechanism. Harris and Raviv (1988) and Stulz (1988) argue the leveraging is an effective takeover defence strategy as it concentrates ownership and increases the percentage ownership of the target's management thus making the firm more costly for a prospective bidder. Garvey and Hanka (1999) find that firms protected by state antitakeover laws substantially reduce their use of debt, while unprotected firms increase their leverage levels. They argue that threat of hostile takeover motivates managers to take on debt they would otherwise avoid. Leveraging can, potentially, be a useful defence tactic in the UK context, where several standard takeover resistance strategies are prohibited. Further empirical support of the use of leverage as a resistance strategy is provided by Billet and Xue (2007) who report that managers threatened by prospective takeovers engage in open market share repurchases funded by new debt issues.

Based on segments A and B, it is hypothesised that there is an inverted U-shape relationship between takeover probability and leverage. A linear relationship fails to reconcile the pecking order theory and inefficient management hypothesis. This is because a direct linear relationship implies that efficiently managed (well-performing high-growth) firms with the ability of reinvesting earnings to generate future growth are more likely to face the threat of takeovers. The nonlinear relationship reconciles key theories including the pecking order theory, management inefficiency hypothesis and the role of debt as a takeover deterrent. The potential existence of a threshold also reconciles seemingly conflicting empirical evidence asserting that targets generally have higher leverage levels than non-targets (Hasbrouck (1985), Bhanot et al. (2010), Ambrose and Megginson (1992), Powell (1997, 2004), Barnes (1998, 1999) and Espahbodi and Espahbodi (2003)) as well as evidence that bidders shun highly levered firms (Harris and Raviv (1988), Stulz (1988) and Safieddine and Titman (1999)). The firm capital structure hypothesis is stated as follows.

> ***Hypothesis 10: Ceteris paribus, there is an inverted U-shaped relationship between a firm's leverage and the probability that it will receive a takeover bid.***

As in Palepu (1986) and Brar et al. (2009), leverage is measured as the ratio of total debt [wc03255] to total equity [wc03995]. This definition of leverage is similar to that used in several prior studies including Palepu (1986), Powell (1997) and Powell and Yawson (2007). The inverted U-shape relationship is captured by adding a (leverage) squared term into the model. A significant positive coefficient for leverage and a significant negative coefficient for leverage squared in the takeover probability model will provide support for the hypothesis.

3.3.4 Financial distress hypothesis

As discussed in section 3.3.3, it is important to consider the implications of an increased likelihood of financial distress (arising from additional debt) in evaluating a firm's takeover probability. It was argued that firms may take on excess debt levels as a way of shielding themselves from future takeovers. This increased debt, nonetheless, engenders a new risk – the risk of bankruptcy or financial distress – when the firm is unable to generate sufficient cash flows to meet its interest commitment. This risk of bankruptcy is likely to be faced mainly by poorly performing firms with high levels of leverage (see, for example, Taffler (1983) and Shumway (2001)). This suggests a potential interaction between leverage, financial distress risk and performance in moderating a firm's takeover risk.

The relationship between a firm's takeover likelihood and its probability of financial distress appears to be unclear. On the one hand, firms with a high likelihood of facing financial distress can be regarded as having inefficient management teams and therefore being suitable takeover targets. These firms are also likely to be more open to takeovers, which, perhaps, is a better alternative to bankruptcy. On the other hand, financial distress caused by excessive leverage might make a firm an unattractive takeover target as the bidder is bound to inherit the debt and debt conditions of the target. More recent bankruptcy studies (e.g., Jones and Hensher (2007)) argue against the use of a binary framework in bankruptcy prediction. The underlying rationale (as discussed in Jones and Hensher (2007)) is that there are different states of financial distress ranging from financial insolvency (in which firms are 'temporarily' unable to meet their financial obligations) to failure or bankruptcy (in which administrators are called-in to begin liquidation proceedings). Jones and Hensher (2007) find that distressed firms that exit the industry through acquisitions have comparatively lower leverage when compared to distressed firms that go into administration, receivership and/or liquidation. The hypothesis is stated as follows.

> ***Hypothesis 11a: Ceteris paribus, takeover likelihood increases with the degree of financial distress.***

The level of financial distress is measured using the Taffler Z score model (Taffler (1983) and Agarwal and Taffler (2007)). The Taffler Z score model is specifically tailored to model the likelihood of financial distress in UK firms. It is worth acknowledging that several limitations of this model have been discussed in prior studies (e.g., Shumway (2001), Chava and Jarrow (2004), Agarwal and Taffler (2007), Christidis and Gregory (2010) and Tinoco and Wilson (2013)). For example, Agarwal and Taffler (2007) find that number of UK firms with low Z scores have dramatically increased post 1997 – suggesting a need to update the model. Chava and Jarrow (2004) find that the use of industry controls substantially improves the model (or model coefficients). Shumway (2001) shows that a 'hazard-type' financial distress model has better predictive power. Notwithstanding, the Taffler model has been widely adopted across several studies as popular alternatives are yet to emerge. Most studies apply the model across different industries. For example Agarwal and Taffler (2007) test the model on a sample of all UK non-financial firms listed on the London Stock Exchange for at least 2 years between 1979 and 2003. The evidence presented by Agarwal and Taffler (2007) asserts the model's applicability to firm's today. The model is shown below (based on Agarwal and Taffler (2007) and Taffler (1983)).

$$Z_i = 3.20 + 12.18X_1 + 2.50X_2 - 10.68X_3 + 0.029X_4 \dots \dots \dots Eqn\ 3.3.4\ (1)$$

Where,

$$X_1 = profit\ before\ tax\ [wc01401]/current\ liabilities\ [wc3101] \dots \dots Eqn\ 3.3.4\ (2)$$

$$X_2 = current\ assets\ [wc02201]/total\ liabilities\ [wc03255] \dots \dots Eqn\ 3.3.4(3)$$

$$X_3 = current\ liabilities\ [wc03101]/total\ assets\ [wc02999] \dots \dots Eqn\ 3.3.4(4)$$

$$X_4 = \frac{(quick\ assets[wc02201 - wc02101] - current\ liabilities\ [wc03101])}{sales\ [wc01001] - PBT[wc01401] - depreciation[wc01151]} \dots \dots Eqn\ 3.3.4\ (5)$$

Per the model, the risk of financial distress decreases with a firm's Z score, with Z scores below 0 indicating insolvency and the likelihood of failure due to financial distress (Agarwal and Taffler (2007)). If the hypothesis (11a) holds, then takeover likelihood should decrease with a firm's Z score. If this is the case, the coefficient of the Z score variable in the takeover probability model, should be positive and significant. To account for the argument that bidders are likely to find highly distressed firms (firm's with Z scores below zero) unattractive, the following hypothesis is tested.

> ***Hypothesis 11b: Ceteris paribus, firms with a high probability of going bankrupt (i.e., firms with Z scores below 0) will have a low takeover probability.***

A Z score dummy variable (ZSDummy) is used to proxy for highly distressed firms. This ZSDummy takes a value of 1 if a firm's Z score is less than 0 and a value of 0, otherwise. If hypothesis (11b) holds, the coefficient of the ZSDummy variable should be negative and statistically significant. The difference between the two hypotheses, 11a and 11b, is that 11a considers Z score as a continuous variable while 11b considers Z score as a binary variable modelling two states of financial distress – solvent and failure.

3.3.5 Firm lifecycle hypothesis

Firm age has been advanced as a factor that affects firm survival[112] within an industry. Agarwal and Gort (1996) discuss several empirical studies (including Jovanovic (1982), Dunne et al. (1989) and Audretsch (1991)) which find a positive relationship between firm age and survival. Jovanic (1982) contends that this relationship is attributable to the fact that, over time, a firm learns about its true costs and relative efficiency and so is less likely to fail. Agarwal and Gort (2002) advanced the literature on firm age and survival by proposing that two key factors (learning-by-doing and firm endowments) define its probability of survival (and hence likelihood of industry exit). Agarwal and Gort (2002) contend that, over time, a firm gains knowledge about itself and its industry, which allows it to achieve cost reductions, product improvements, and develop new market techniques – learning-by-doing. In terms of endowments, Agarwal and Gort (2002) argue that firm endowments[113] are generally low when firms are born, but increase over time as firms invest in research and development. Older firms are therefore more endowed and more knowledgeable about themselves. The implication is that the probability of firm survival within an industry increases as firms grow older, learn about themselves and improve their endowments.

Based on the lifecycle theory, Loderer and Waelchli (2010) argue that when firms grow old (after maturity) they are forced to turn to other firms for help. This is because they become increasingly rigid, less dynamic[114], profitable and innovative (Leonard- Barton (1992)). They also become technologically obsolete in terms of products and services and are forced to initiate or accept takeovers (Davis and Stout (1992) and Loderer and Waelchli (2010)). Their takeover likelihood therefore increases with age after a threshold. Jensen (2000) adds that, old firms can also constitute attractive targets as they house resources trapped within outdated structures which can be freed by a successful bidder through takeovers. In line with Loderer and Waelchli (2010), Agarwal and Gort (2002) contend that obsolescence rises with firm age, leading to a net negative investment in endowment in very old firms. At this point, the probability of survival starts to decline. The outcome of

112 Theories on the effects of firm age on firm outcomes have mostly been discussed in the literature on firm survival. Takeovers are the main survival hazard faced by firms (Loderer and Waelchli (2010)). That is, many firms exit the industry (or fail to survive) due to takeovers.

113 Endowment is defined as a firm's inherent or natural suitability for profitability.

114 Leonard-Barton (1992) argues that as firms grow older, there is the tendency for them to concentrate on their core capabilities. This limits their ability to adapt to shocks in the business environment.

both contentions is an inverted U-shaped relationship between firm age and probability of survival.

There is substantial empirical evidence showing that younger firms face a higher risk of acquisition (see, for example, Zingales (1995) and Loderer and Waelchli (2010)). This relationship is explained by the observation that many entrepreneurs use initial public offerings as an exit strategy. Further, young firms are, perhaps, more attractive takeover targets as they have fresh resources, new business models, new technologies, innovative products and are founded on more contemporary business ideas. They may thus constitute an attractive investment option for mature firms seeking to pursue new business opportunities and expand their product portfolios. Agarwal and Gort's (2002) theory of firm survival does not, however, consider the unique drivers of different survival hazards (including bankruptcy, takeovers and delisting) faced by firms. While Agarwal and Gort's (2002) empirical results support the hypothesis, the coefficient of the independent age variable (age square) which proxies for 'old firms' is low, indicating that the relationship might not be as strong as suggested. Further, Shumway (2001) finds no evidence relating firm age to probability of bankruptcy. In line with Loderer and Waelchli (2010), both findings suggest that the main survival hazard faced by firms is the threat of takeovers. If this is the case, then the takeover likelihood should, perhaps, be a U-shaped function of firm age. The hypothesis is stated as follows.

> ***Hypothesis 12: Ceteris paribus, takeover probability is a U-shaped function of firm age i.e., takeover likelihood initially decreases with age then increases as firm age exceeds a threshold.***

The choice of a suitable proxy for firm age (listing age or incorporation age) has been discussed in 3.2.9. The incorporation age (computed from the year of firm incorporation [wc18273]) has been chosen in this study. The hypothesised U-shaped relationship is tested by adding a squared term for firm age. It is expected that if the hypothesis holds, takeover probability should have a negative relationship to firm age and a positive relationship with firm age squared.

3.3.6 M&A rumours hypothesis

Despite the perceived obvious relationship between rumours on takeovers and takeover probability of rumoured targets, there has been, to my knowledge, no empirical research looking at the ability of takeover rumours to predict future takeovers. The prediction potential of takeover rumours will be investigated here for the first time. Oberlechner and Hocking (2004) define rumours as 'allegations which are passed along accompanied by doubt rather than by evidence' (p. 420). They argue that rumours bear the characteristics of news since rumours may be positive or negative and rumours explain important events. In their interviews with trading experts, they find that trading experts have to evaluate the validity of every piece of information (rumour) they received in order to outperform the majority of market participants who 'just assume the news (rumour) is correct' (p. 421). Inferring from this claim, one can argue that a robust takeover prediction model which incorporates but does not entirely depend on takeover rumour information, might provide a way of making 'sense' out of rumours.

Bommel (2003) examines an informed investor's motivation for spreading stock tips or rumours. He notes that since rumours are imprecise in nature, there is a likelihood that prices will be positively biased allowing the rumourmonger the opportunity to carry out two profitable trades – first when the rumourmonger has private information and next when the market overreacts. Bommel (2003) finds that rumours are informative at equilibrium, thus allowing rumourmongers (as well as their followers) to outperform uninformed investors. The main problem is, perhaps, the fact that rumours might carry honest information, no information or contrary information. Bommel (2003) shows that rumourmongers are more likely to spread honest rumours due to the moral hazard associated with bluffing or cheating. A rumourmonger who bluffs or cheats will benefit from 'deceiving' the market in the first instance, but will be unable to 'sell' rumours in the future.

Pound (1990) investigates the effects of takeover rumours from the 'Heard on the street' column of the Wall Street Journal (WSJ) on stock prices. Pound concludes that the market is efficient in responding to this information as no significant returns can be made from investing in rumoured targets once the rumours are published. Pound finds that more than 40% (18 out of 42 firms) of the rumoured targets in their sample actually received a bid within one year of the publication. In their study of 362 tender offers between 1981 and 1995, Jindra and Walking (2004) find that 7% of the takeovers are preceded by rumours. In line with the contention that rumours are informative at equilibrium (Bommel (2003)) and the finding that several tender offers are preceded by rumours (e.g., Pound (1990) and Jindra and Walking (2004)), it is hypothesised that:

Hypothesis 13: Ceteris paribus, a firm's takeover probability increases with the presence of rumours about the firm becoming a prospective takeover target.

I propose the use of a merger rumour dummy variable (MRDummy) which takes a value of 1 when there are rumours about the potential takeover of a firm in the past year and a value of 0, otherwise. As will be discussed in chapter 4, Thomson OneBanker is used to collect data on M&A rumours over the period.

3.3.7 Payroll synergies hypothesis

The potential for mergers to create synergies is generally advanced by managers as the main rationale for engaging in mergers. These synergies appear to mainly be generated through cutting operating costs (Devos et al. (2009)), which mostly constitute personnel costs (see, for example, Haynes and Thomson (1999) and Shleifer and Summers (1988)). Haynes and Thomson (1999), reviewing the case of UK mutual funds, find that takeovers are followed by three years of negative effects on the demand for labour. This finding – a decline in demand for labour post acquisitions – has been replicated across different studies employing different samples (see, for example, Conyon et al. (2002), Kubo and Saito (2012) and Lehto and Bockerman (2008)). Shleifer and Summers (1988) argue that much of the benefits to merging firms come from the termination of long term contracts with employees. After investigating nine bank mergers in the US, Rhoades (1998) finds that staff reduction constituted the largest element of cost reduction and synergy creation in bank mergers. In his sample, on average, over 50% of total cost savings post-merger are in payroll reductions (Rhoades (1998)). The evidence therefore suggests that payroll savings constitutes one of the main forms through which synergy can be achieved through mergers. To the best of my knowledge, no study has investigated how the payroll costs, given its role in the generation of synergies, affects a firm's takeover propensity.

Capron (1999) argues that two types of synergies (cost synergies and revenue-enhancing synergies) are created through mergers. Cost synergies are generally achieved through asset divestitures (including personnel cutbacks) while revenue-enhancing synergies are achieved through the efficient redeployment of resources (physical assets and personnel) to improve corporate earnings (see Capron (1999)). Other studies (see, for example, Comment and Jarrell (1995), Walker (2000) and Houston et al. (2001)) corroborate this framework. In line with the cost synergies and revenue-enhancing synergies perspective, it is hypothesised here that takeover likelihood will increase with the availability of payroll synergies (such as the redeployment of resources) until such a point where creating synergies is unlikely (perhaps due to the need for very large layoffs). In essence, payroll synergies can be achieved through a combination of human resource (HR) asset redeployment (efficient utilisation of the target's HR resources) and HR asset divestiture (employee layoffs). The bidder's propensity to generate synergies will, perhaps, increase with the presence of excess human resources in the target. Nonetheless, at high levels (excess human resources) negative synergies are created as the costs and reputational effects of asset divestitures become too high. The hypothesis therefore argues that takeover likelihood has an inverse U –shaped relationship with HR costs.

Firms with a high payroll cost (or payroll burden) relative to other firms are likely to have a high takeover likelihood due to the potential cost synergies to be created by a bidder. Gugler and Yurtoglu (2004) find that the UK (and Europe as a whole) has a high labour-adjustment cost[115] when compared to the US. This is mainly because the European employment regulations provide stricter employment protection making it comparatively more difficult to lay-off staff, particularly through collective dismissals (Gugler and Yurtoglu (2004)). This suggests that some firms carry excess labour due to the challenges (e.g., litigation) and costs (e.g., compensation and corporate reputation) of firing employees. Shleifer and Summers (1988) and Gugler and Yurtoglu (2004) note that corporate reorganisation through M&A is an effective way of achieving the desired restructuring (at least, in Europe) as a new management team is less likely to uphold existing employee contracts. The transfer of corporate ownership, perhaps, also provides a strong argument for engaging in restructuring initiatives such as layoffs. Their evidence (Shleifer and Summers (1988) and Gugler and Yurtoglu (2004)) suggests that firms can deliberately engage (as a target) in M&A to create shareholder value by shedding their excess human resources. Such a transaction also presents bidders with an opportunity to generate operational synergies through increased target efficiency.

Further, firms with higher technological knowhow (such as the mechanisation of manual processes) are, potentially, able to earn rents from this knowledge and capability by acquiring labour intensive firms and shedding the excess human resources [116]. Given the empirical finding that a reduction in payroll costs is one of the main ways of generating synergies in mergers (Devos et al. (2009), Haynes and Thomson (1999) and, Shleifer and

115 Labour adjustment cost is the cost of maintaining an optimal work force by firing excess staff.
116 These rents could be in terms of cost savings and synergies generated by employing advanced technologies to mechanize manual processes thus eliminating the need to hold staff.

Summers (1988)), one can predict that, other things being equal, a firm's takeover likelihood is likely to increase with its payroll costs.

Nonetheless, it is unlikely that this relationship will persist in a linear fashion. While the redeployment and divestment (layoffs) of human resources can be a way to create synergies, the associated costs (e.g., compensation and reputational effects) might result in the creation of negative synergies at very high levels (Krishnan et al. 2007). Besides increasing the complexity of the restructuring process, very large layoffs are likely to lead to significant or costly compensation schemes. Such layoffs are also likely to be met with stiff resistance from managers and employees with further effects on retained employee motivation and performance. Further, protracted litigations and court battles with damaging effects on corporate reputation cannot be ruled out. These arguments suggest that despite the potential for synergies, takeover likelihood will, perhaps, decline with payroll costs when the target has very high levels of payroll costs. This suggestion is consistent with Pagano and Volpin (2005) who argue that managers can use high employee wages and long-term contracts as a strategy to defend against unwanted takeovers. The implication is an expectation of an inverse U-shaped relationship between corporate payroll and takeover probability. The hypothesis can be stated as follows.

> ***Hypothesis 14: Ceteris paribus, takeover probability is an inverse U-shaped function of a firm's payroll burden.***

To my knowledge, neither this hypothesis nor any hypothesis relating a company's payroll burden to its takeover probability has been tested in prior research. Payroll burden is proxied by the ratio of payroll expenses (i.e., salaries and benefits expenses – wc01084) to total sales (wc01001). This ratio indicates the percentage of revenue that is allocated to employees in wages. A high percentage indicates a greater or more significant payroll burden to the company. If this hypothesis holds, takeover probability should have a negative relationship with payroll cost and a positive relationship with the square of payroll cost.

3.3.8 Share repurchases hypothesis

Firms sometimes engage in share repurchase programmes during which they buy back their shares from current shareholders. As the literature asserts, the use of share repurchases has increased significantly over the past two decades (Billett and Xue (2007) and Grullon and Michaely (2002)) and fewer firms are paying dividends over time (Fama and French (2001)). The contention therefore is that share repurchase programmes are being used as a preferred means of distribution of excess cash to shareholders over dividends (Grullon and Michaely (2002)). A large body of literature asserts that share repurchases play several roles including the distribution of free cash flows, signalling of firm undervaluation, firm capital structure readjustment and takeover defence strategy (see, for example, Harris and Raviv (1988), Persons (1994), Jagannathan et al. (2000), Dittmar (2000), Grullon and Michaely (2002, 2004), Brav et al. (2005) and Billett and Xue (2007)).

In Harris and Raviv’s (1998) model, firms defend against takeovers by issuing debt and using its proceeds to engage in share repurchases activity. Bagwell (1991) shows that share repurchases deters takeovers by reducing heterogeneous valuations amongst shareholders. Once a repurchase offer is made, those shareholders who perceive the value of their shares to be low will tender their shares for repurchase while those shareholders who perceive their shares to be of higher value will hold on to their shares (Bagwell (1991)). This deters takeovers by eliminating shareholders with a low perceived value, thus increasing the cost to be incurred by any potential bidder. Further, share repurchases effectively reduces the number of shares in free float. Harris and Raviv (1988) and Persons (1994) add that shares become concentrated amongst institutional shareholders and other major shareholders (friendly shareholders) who are less likely to succumb to a takeover by tendering their shares.

The finding that firms are substituting dividends for share repurchases (Fama and French (2001)) indicates that share repurchases are also used to distribute excess free cash flows. This should reduce the agency problem (Jensen (1986)) and hence the firm’s takeover likelihood. Grullon and Michealy (2004), for example, find that the market reacts positively to share repurchase announcements due to its role in reducing free cash flow. Given the finding that share repurchases serves as a deterrent to takeovers and reduces agency problems, it is hypothesised that takeover probability should decline with the presence of share repurchase activity. The hypothesis is stated as follows.

> ***Hypothesis 15a: Ceteris paribus, takeover probability will decline when a firm engages in share repurchase activity.***

Another perspective on share repurchases – the information-revealing hypothesis – is that, share repurchases signal a manager’s private information about the favourable future prospects of the firm, and hence, firm undervaluation[117]. A survey conducted by Brav et al. (2005) reveals that firm undervaluation is the key factor driving the decision to repurchase shares. While some studies (Vermaelen (1981), Comment and Jarrell (1991), Ikenberry et al. (1995), Grullon and Michaely (2004), and Peyer and Vermaelen (2005)) have shown that the market reacts positively to share repurchase announcements thus leading to an instantaneous increase in firm value, there is overwhelming evidence that the market, on average, underreacts to share repurchase announcements (see, for example, Ikenberry et al. (1995, 2000), Mitchell and Stafford (2000), Chan et al. (2004), McNally and Smith (2007), Peyer and Vermaelen (2009) and Yook (2010))[118].

Given the magnitude of the gains generated in the years following the repurchase announcement, it is probable that some of these gains can be explained by takeover activity involving repurchasing firms. In line with the undervaluation hypothesis (section 3.4.3), a firm which is potentially undervalued by the market constitutes an attractive target to a prospective bidder. A share repurchase highlights the likelihood that a firm is undervalued, thus, potentially, increasing its likelihood of receiving a bid. The evidence shows that the market systematically under-reacts to share repurchase announcements, implying that the bidder is would still be able to benefit from firm undervaluation post share repurchase announcements. It is therefore hypothesised that repurchases announcement reveal information on firm undervaluation and thus increases the firm's takeover likelihood. The hypothesis can be stated as follows.

> ***Hypothesis 15b: Ceteris paribus, takeover probability will increase when a firm engages in share repurchase activity.***

Hypothesis 15a and 15b are competing hypothesis with contradictory predictions on the relationship between takeover probability and the share repurchases. The two hypotheses are, nonetheless, justified on different theoretical bases. The results obtained will therefore shed some light on the effect of share repurchases on takeovers. A dummy variable is used as a proxy to capture the presence or absence of share repurchases announcements in the

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117 See, for example, Bhattacharya (1979), Miller and Rock (1985), Dann (1981), Vermaelen (1981, 1984), Lakonishok and Vermaelen (1990), Hertzel and Jain (1991), Comment and Jarrell (1991) and Dann et al. (1991).

118 Ikenberry et al. (1995), for example, find that undervalued firms repurchasing shares generate average abnormal returns of 45.3% in the four years following the repurchase announcement. This long run return far exceeds the reported average share repurchase announcement return of about 3.0% (see, for example, Vermaelen (1981), Comment and Jarrell (1991) and Ikenberry et al. (1995)). These systematic substantial long run gains (beyond initial market reaction) have been described as an anomaly (see Peyer and Vermaelen (2009)) as its source is still unclear.

past year. The share repurchase dummy variable (SRDummy) takes a value of 1 in this period (year *t*) when there has been a share repurchase activity in the prior year (1^{st} July year *t*-1 to 30^{th} June year *t*) and a value of 0, otherwise. The chosen period (1^{st} July to 30^{th} June) is explained by the fact that the June approach is used in the formation of portfolios in this study (further discussed in chapter 4). Data on Share repurchase announcements, including the announcement date and the magnitude of the repurchase activity is available from Thomson OneBanker. A significant negative coefficient of the SRDummy will indicate empirical support for hypothesis 15a while a significant positive coefficient will provide some empirical support for hypothesis 15b.

3.3.9 Asymmetric valuation hypothesis

The asymmetric valuation hypothesis (in this study) builds on the popular information asymmetry hypothesis. Information asymmetry arises when agents have unequal access to information required to make an informed decision such that one party relies on probabilities of the true state. The role played by information asymmetry – the information asymmetry hypothesis – has been studied in several contexts. Krishnaswami and Subramaniam (1999), for example, use the information asymmetry hypothesis to explain why corporate spin-offs (and not many other restructuring activities) create value for shareholders. They argue that spin-offs create value as the restructuring of a firm into smaller more focused units allows investors to understand the position of the firm – by reducing the information asymmetry between the firm and its investors. Their results show that the gains from spin-offs are positively related to the level of information asymmetry before the spin-off.

The role of information asymmetry in M&A decision making has been explored by prior researchers. Draper and Paudyal (2008), for example, show that bidders engage in acquisitions to reduce information asymmetry between themselves and the market. They argue that besides the investment implications (e.g., synergies created) of the bid, M&A bids spurs investors to reassess or revalue the bidder. Their results show that the returns to bidders gradually decrease with successive bids. They associate this decrease with a decline of the level of information asymmetry between bidders and investors with successive bids. In summary, this study shows that information asymmetry negatively impacts on firm value.

Hansen (1987) argues that it is optimal for bidders to use stock as acquisition currency when the level of information asymmetry between target and bidder is high. This is because the use of stock allows the bidder to share the risk of acquiring the target with target shareholders (Hansen (1987) and Martynova and Renneboog (2009)). This contention is supported by the finding that bidders earn more from acquisitions of opaque targets when stock (rather than cash) is used to finance the deal. Consistent with this argument, Officer et al. (2009) also contend that bidders gain more from acquisitions when they use stock as transaction currency when acquiring difficult-to-value takeover targets. Here, the use of stock as a method of payment appears to mitigate some of the problems caused by information asymmetry (Officer et al. (2009)). This evidence suggests a link between information asymmetry and the value creation from M&A activities.

Despite the substantial research on the causes and consequences of information asymmetry, there is little established theory on how information asymmetry moderates a firm's (or prospective target's) takeover likelihood. To my knowledge, no prior study has directly considered how information asymmetry moderates a firm's acquisition likelihood. I anticipate that, on average, bidders will prefer to acquire targets which they understand – low information asymmetry between target and bidder. This is, perhaps, the case as information asymmetry will lead to difficulties in the valuation of targets by the bidder. Here, I present a framework to illustrate that information asymmetry between the target and bidder (pre-merger), potentially, leads to a reduction in the post-merger value of the combined firm. My argument is consistent with Krishnaswami and Subramaniam (1999) who suggest that information asymmetry between a firm's insiders and its investors leads to a depletion in firm value. If this is the case, then from a neoclassical stance, information asymmetry should reduce a firm's likelihood of receiving a bid (from a value maximising bidder), all things being equal. I also anticipate that the size of the reduction of post-merger value is, perhaps, directly related to the level of information asymmetry. That is, the size of the post-merger value of the combined firm is inversely related to the information asymmetry between the target and the bidder. This therefore yields an inverse relationship between takeover likelihood and target information asymmetry. This is illustrated below.

By definition, synergies (V_s) are created when the value of the combined firm or the value of the bidder post-merger (V_c) exceeds the sum of the value of the target (V_t) and bidder (V_b) pre-merger. This sum is given by $(V_b + V_t)$. V_b and V_t are the intrinsic values of the bidder and the target (respectively) known to their managers. The bidder evaluates the target as part of the merger process and assigns the target a value, (V_x). It can be assumed that $V_x = V_t$ when there is no information asymmetry between the bidder and target management. That is, the bidder's valuation of the target is equal to the target's intrinsic value (i.e., its true value excluding any potential synergies created through a merger). However, when there is information asymmetry between bidder and target management, $V_x - V_t > 0$. That is, bidder's valuation of the target will be higher than the target's intrinsic value. With information asymmetry, the bidder systematically over-values (but never undervalues) the target. $V_x - V_t < 0,$ is not observed (on average) as the target's management is unlikely to accept any bids below the intrinsic value of the target.

A proportion of the value created through the merger is shared with the target shareholders through the payment of a merger premium $\left(V_p\right)$. The value of the combined firm, irrespective of the method of payment (cash, equity or mixed), is (V_c), where

$$V_c = V_b + V_s + V_t - V_x - V_p \dots\dots\dots Eqn\ 3.3.9\ (1)$$

That is, the post-merger value of the combined firm is equal to the sum of the value of the bidder (V_b), the value of synergies created (V_s) and the value of the target (V_t) less the bidder's valuation of the target (V_x) and the acquisition premium paid by the bidder $\left(V_p\right)$[119]. Eqn 3.3.9 (1) could be rearranged as follows.

$$V_c = V_b + V_s - (V_x - V_t) - V_p \dots\dots\dots Eqn\ 3.3.9\ (2)$$

$(V_x - V_t)$, which is the difference between the target management's valuation and the bidder's valuation, is an overpayment due to information asymmetry. This difference, perhaps, increases with the level of information asymmetry. That is, the bidder is likely to highly overvalue a more opaque target than a less opaque target[120]. When there is no information asymmetry, i.e., where$(V_x - V_t) = 0$, the value of the combined firm $({V^0}_c)$ is simply the sum of the value of the bidder (V_b) and the value of synergies created (V_s) minus the merger premium$\left(V_p\right)$.

$${V^0}_c = V_b + V_s - V_p \dots\dots\dots Eqn\ 3.3.9\ (3)$$

When information asymmetry causes asymmetric valuation, i.e.,$(V_x - V_t) > 0$, the value of the combined firm $({V^i}_c)$ is given by its value when there is no information asymmetry

119 The sum of the bidder's valuation of the target and the acquisition premium paid by the bidder is the offer price.

120 This assumption is consistent with Officer et al. (2009) who find evidence that more opaque firms are more difficult to value.

($V^0{}_c$, as shown in equation 3.3.9(3)) less the overpayment due to information asymmetry ($V_x - V_t$).

$$V^i{}_c = V^0{}_c - (V_x - V_t) \dots \dots \dots Eqn\ 3.3.9\ (4)$$

The illustration shows that information asymmetry between the bidder and target potentially leads to a reduction in the bidder's post takeover value (or value of combined firm), with the value-reduction increasing with target opaqueness or the level of information asymmetry. Based on this illustration, it is hypothesised that bidders are likely to be attracted to targets where the level of information asymmetry between bidder and target management is likely to be low as this results in a higher post-merger value. The hypothesis is stated below.

Hypothesis 16: Ceteris paribus, takeover probability will decrease as the level of target information asymmetry increases.

Measuring opacity is a major challenge as information asymmetry can be considered as a multidimensional construct. For example, information asymmetry can arise from the target's accounting quality, asset structure and operational strategy and might also depend on the bidder's knowledge of the target's industry. Arguably, there is currently no comprehensive proxy for information asymmetry. Some prior studies (such as Aboodi and Lev (2000), Officer et al. (2009) and Ciftci et al. (2011)) proxy the degree of a firm's opacity – the level of information asymmetry between the firm and a prospective bidder – using its research and development (R&D) intensity. Firms with high levels of R&D are, perhaps, difficult to value as their future cash flows are a function of the success of their R&D programmes – which is uncertain at best. I explore the use of this measure but find that several firms in the UK sample do not report R&D values in the early periods of the study. Many firms do not also generally engage in R&D activities. Consistent with Shah et al. (2013) the data for R&D is also likely to be inconsistent over time due to changes in accounting regulation particularly the adoption of IFRS by UK listed firms after 2005.

Krishnaswami and Subramaniam (1999) suggests five different measures of information asymmetry including forecast error in earnings, the standard deviation in analysts' forecasts, a normalised forecast error, volatility in abnormal returns around earnings forecast and residual volatility. The data on analysts' earnings forecasts over my sample period is patchy and a large proportion of some firms in the sample have no analyst coverage during the period. Consistent with other studies such as Bhagat et al. (1985), Blackwell et al. (1990), Krishnaswami and Subramaniam (1999) and Krishnaswami et al. (1999), I adopt residual volatility as the preferred measure of information asymmetry – the level of asymmetry in target valuation – in this study. As suggested by Krishnaswami and Subramaniam (1999), residual volatility is measured as 'the dispersion in the market-adjusted daily stock returns' in the year to June 30th (prior to the takeover).

The level of asymmetry in the valuation of targets is high when target managers hold significant value-relevant firm-specific private information. Krishnaswami and Subramaniam (1999) suggests that if all stakeholders are equally well-informed about all factors that moderate firm value then residual standard deviation or volatility in excess returns should capture the level of information asymmetry between stakeholders. This variable captures any firm-specific uncertainty that persists after excluding the total uncertainty shared by all stakeholders. Firms with higher information asymmetry about their value are likely to have a higher residual volatility in stock returns (Krishnaswami and Subramaniam (1999).

The procedure for computing residual volatility is similar to that used to compute ADAR in section 3.2.1. First, daily abnormal returns (DAR) are computed from daily price index data [RI] using the OLS market model (discussed in Brown and Warner (1980, 1985)). The model for the computation of the DAR is given as follows;

$$DAR_{it} = R_{it} - \left(\widehat{\propto}_i + \hat{\beta}_i R_{mt}\right) \ldots\ldots\ldots \textit{Eqn 3.3.9 (1)}$$

Here, DAR for a firm *i* at time *t* is given by the difference between the firm's actual stock return at time *t* and its expected stock returns at time *t* (given by $\left(\widehat{\propto}_i + \hat{\beta}_i R_{mt}\right)$). The returns for each firm *i* on day *t* (denoted R_{it}) and the market *m* on day *t* (denoted R_{mt}) are first computed from adjusted price [RI] as follows.

$$R_{it} = (RI_{it} - RI_{it-1})/(RI_{it-1}) \ldots\ldots\ldots Eqn\ 3.3.9\ (2)$$

$$R_{mt} = (RI_{mt} - RI_{mt-1})/(RI_{mt-1}) \ldots\ldots\ldots Eqn\ 3.3.9\ (3)$$

The daily return of the FTSE All-Share (R_{mt}) is used as a proxy for the daily market returns. Next, $\widehat{\propto}_i$ and $\hat{\beta}_i$ are estimated by using data in the previous period (260 trading days). Each firm's daily stock returns in period *T-1* (previous period)[121] is regressed on its daily market returns in period *T-1* and the coefficients of the regression model are used as

[121] As will be fully discussed in chapter 5, each period is considered to run from 1st July year 1 to 30th June year 2.

estimates of $\hat{\propto}_i$ and $\hat{\beta}_i$. The regression coefficients ($\hat{\propto}_i$ and $\hat{\beta}_i$ estimates) from period *T-1* are used to compute DAR in the next period (period *T*). The residual volatility of firm *i* in period *T* is given by the standard deviation of DAR_{it}.

3.3.10 Industry concentration hypothesis

A concentrated industry is one which consists of a few dominant firms or an oligopolistic industry structure. These few firms generally control a large proportion of the market share and hence enjoy a high market power. High concentration industries generally have high barriers to entry for newcomers. Barriers to entry can come as a result of high advertising from incumbents, the need for high start-up capital, cost advantages to incumbents (in the form of proprietary technology, experience, distribution networks), high degree of customer loyalty (or high switching barriers for customers in the form of contracts), government policy (protected industries), intellectual property rights (patents and trademarks) and inelastic demand, amongst others. Further, mergers in high concentration industries are generally contentious and the subject of antitrust regulations in Europe, the US, Canada and Australia, amongst others. These antitrust regulations reduce the likelihood that incumbent firms within such high concentration industries will be subject to takeover activity.

Given the limited number of market players, the level of competition between firms in high concentration industries is comparatively lower than that in low concentration industries. The effect of industry concentration on the market for corporate control, the incidence of takeovers and the agency problem has been discussed by several researchers[122]. Prior research argues that strong competition in the product markets (i.e., low industry concentration) is especially costly for inefficiently managed firms (see, for example, Fama and Jensen (1983) and Shleifer and Vishny (1997)). This is mainly because competition between firms in a low concentration industry leads to the elimination of inefficiently managed and under-performing firms.

As opposed to firms in high concentration industries, firms in low concentration industries have limited control of the market, restricted market share, and a low market power. Powell and Yawson (2005) suggest that low concentration industries are more likely to see

[122] See, for example, Alchian (1950), Stigler (1958), Fama (1980) and Fama and Jensen (1983), Holmstrom (1999), Nalebuff and Stiglitz (1983), Hart (1983) and Cremers et al. (2008), amongst others.

higher takeover activity as incumbents (prospective bidders) compete to gain a greater share of the market. Again, struggling firms can solicit takeovers either as an alternative to impending bankruptcy (financial distress) or as a way of improving their market power and ability to compete more efficiently. Further, antitrust regulators are less likely to oppose mergers within low concentration industries. It can therefore be hypothesised that, all things being equal, a firm's takeover likelihood will increase as the concentration of its industry decreases (or the competitiveness of its industry increases). The hypothesis is stated below.

> ***Hypothesis 17: Ceteris paribus, takeover probability will decrease as the concentration of a firm's industry increases.***

In the current study, the Herfindahl-Hirschman index (HHI) is used as a proxy for industry concentration. This measure of industry concentration is popular and has been used in studies such as Hou and Robinson (2006), Giroud and Mueller (2010) and Loderer et al. (2011). The identification of industries in this study is discussed in section 4.2.2. Unlike other measures of concentration (e.g., the four firm concentration ratio), the HHI considers the entire distribution of industry market share information thus leading to a more comprehensive measure of industry concentration (Hou and Robinson (2006)). Consistent with these prior studies (Hou and Robinson (2006) and Giroud and Mueller (2010)), the index is computed as the sum of the squared market shares of all publicly listed firms in the industry. Market share is computed as the proportion of a firm's revenue [wc01001] to the industry's revenue (sum of [wc01001] for all publicly listed firms (*n*) in the industry (*j*) during a specific period, *t*). The index is computed using the formula below.

$$HHI_J = \sum_{i=1}^{n} \left(\frac{Rev_{it}}{\sum_{i=1}^{n} Rev_{it}} \right)^2 \ldots \ldots \ldots Eqn\ 3.3.10\ (1)$$

Low values of HHI indicate a low industry concentration, i.e., an industry in which the market is shared by several competing firms, and vice versa (Hou and Robinson (2006)). Hou and Robinson (2006) and Giroud and Mueller (2010) have shown that measures of market shares which employ total assets or total equity are highly correlated to measures which employ firm revenue.

Arguably the measurement of HHI in this study is biased as it ignores the contributions of privately listed firms which are likely to play a significant role or control a substantial market share in certain industries. As will be discussed in chapter 4, the study relies on data obtained from DataStream which only holds data for publicly listed companies. Some data for private companies is available on FAME but the period of coverage is limited (10 years) and does not cover the full period of this study. While the reliance on data for public listed companies only, is in line with prior studies (including Hou and Robinson (2006) and Giroud and Mueller (2010)), it is worth acknowledging that this constitutes a limitation of the current study and an opportunity for further research.

3.3.11 Market liquidity hypothesis

When the number of deals and the total value of deals are considered, it is generally accepted that mergers occur in wavelike patterns (see, for example, Martynova and Renneboog (2008) and Rhodes-Kropf and Viswanathan (2004)). Martynova and Renneboog (2008) document five historical merger waves (including, mergers waves of the 1900's, 1920's, 1960's, 1980's, and 1990's) and anticipate the beginning of a new wave after 2003. Martynova and Renneboog (2008) note that the fifth wave (which was the most recent, completed and documented merger wave) covered four main regions (including the US, UK, Asia and Europe). Martynova and Renneboog (2008) argue that the wave was primarily driven by the communication and information technology industry and was precipitated by economic/financial markets boom and globalisation processes (such as technological innovation, deregulation and privatisation).

The end of the fifth wave coincides with the stock market crash (Dotcom crises) and the 'September 11' terrorist attack in the US. Compelling empirical evidence (see, for example, Mitchell and Mulherin (1996), Andrade et al. (2001), Andrade and Stafford (2004), Martynova and Renneboog (2008), and Gorton et al. (2009)), suggest that takeovers are most likely to occur in periods of economic recovery, coinciding with rapid credit expansion, burgeoning external capital markets and stock market booms. The evidence also suggests that waves are frequently driven by industrial and technological shocks with regulatory changes (such as antitrust legislation and deregulation) acting as a catalyst and stock market declines acting as inhibitors to takeover activity (see, for example, Martynova and Renneboog (2008) and Rhodes-Kropf and Viswanathan (2004)).
M&A transactions are generally high capital investments and hence rapid credit expansions are likely to stimulate M&A activity (see, for example, Martynova and Renneboog (2008) and Rhodes-Kropf and Viswanathan (2004)). The methods of payment employed in mergers include: cash, equity and a mixture of both. Prior empirical evidence

suggests that a high proportion of M&A transactions involve the use of cash (see, for example, Danbolt (2004) and Danbolt and Maciver (2012)[123]. Even in circumstances where equity is used as the preferred method of payment, bidders will, perhaps, still require substantial cash resources to successfully absorb the target and complete post-merger reorganisation activities. Perhaps, the majority of firms are unlikely to have sufficient internally generated cash resources to complete takeovers without relying on external funding either from equity markets or from debt markets.

The success of M&A activities is therefore likely to be contingent on the availability of capital and the ease at which capital can be obtained. This suggests that takeovers are more likely to occur in periods of high capital availability and market liquidity. Historical evidence affirms that more mergers are completed in periods of economic expansion than in periods of economic gloom (Harford (2005) and Maksimovic and Phillips (2001)). Prior research suggests that merger waves result from economic, technological and regulatory shocks (Gort (1969) and Mitchell and Mulherin (1996)) with high capital availability and high macro level liquidity acting as important catalysts (Harford (2005)). Macro level liquidity – the availability or ease of obtaining investment capital – appears to play a major role in moderating takeover activity. It is hypothesised that, all things being equal, more mergers will be observed in periods of high macro level liquidity or high investment capital availability. The hypothesis is stated as follows.

> ***Hypothesis 18: Ceteris paribus, takeover probability will increase with market liquidity.***

Market liquidity attempts to measure the flow of funds, the ease of raising capital and the cost of capital within the UK market – availability of M&A investment capital. Market liquidity is computed as the difference between the 12-month London Interbank Offer Rate (LIBOR) and the Bank of England Base Rate (BOEBR).

$$Market\ Liq_t = LIBOR_t - BOEBR_t \ldots \ldots \ldots Eqn\ 3.3.11\ (1)$$

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123 In a UK study, Danbolt (2004), for example, finds that over 95% (of 116) foreign bidders and 30% (of 510) domestic bidders use cash as the preferred method of payment. For the domestic bidders not using solely cash as a method of payment, over 9% use cash alongside other forms (equity and alternatives) as the method of payment. Danbolt and Maciver (2012) also show that UK bidders have a high preference for cash over other methods of payment, with 44.6% of bidders paying in cash and 45.4% using a mixed method. Danbolt and Maciver (2012) find that only 10% of UK bidders use equity exchange as the method of payment.

Rate changes from one month to the other are fairly slight. I therefore consider the average of the reported monthly rates over each year-ending June 30th (i.e., 1 July year *t* to 30 June year *t*+1) as the annual LIBOR and BOEBR. The choice of period 1 July year *t* to 30 June year *t*+1 is explained by the portfolio formation strategy – the June approach – further discussed in chapter 4. A smaller spread indicates high capital availability over the period and thus a, potentially, higher acquisition propensity in the subsequent period. A similar measure of market liquidity has been used by Harford (2005). Harford's measure of market liquidity is the spread between the commercial and industrial loan rate and the US Federal Reserve Funds rate.

3.3.12 Market economics hypothesis

Investment decisions are sometimes driven by factors beyond firm and economic fundamentals. Helwege and Liang (1996), for example, argue that investor reaction to corporate announcements are driven by investor sentiments, with more positive reactions observed in periods of high investor sentiments and vice versa. Also, more merger deals are completed during periods of high stock market valuation (Shleifer and Vishny (2003) and Dong et al. (2006)). Maksimovic and Phillips (2001) and Harford (2005) show that merger activity generally increases in periods of economic growth (booms) and declines in periods of recession (downturns). This trend could be interpreted as an attempt by bidders to take advantage of their overvalued stocks, in the case of stock deals (Rhodes-Kropf and Viswanathan (2004) and Dong et al. (2006)) or the observation that economic growth increases the likelihood of mergers being successful (Harford (2005)). This trend is also consistent with merger wave theories (see, for example, Martynova and Renneboog (2008) and Rhodes-Kropf and Viswanathan (2004)) discussed in section 3.3.11 above.

There is, therefore, likely to be a positive correlation between economic performance and stock market activity, which I attribute to market sentiment about success of investment projects. Again, economic growth opens up new market opportunities. Such market opportunities are likely to be short-lived due to the cyclical nature of economic performance – with periods of growth interspersed by periods of decline. The evidence, however, suggests that managers are not deterred by the knowledge of impeding market declines, as M&A activities systematically increase in periods of market growth (Maksimovic and Phillips (2001) and Harford (2005)). Managers can, perhaps, benefit from transitory growth periods in economic cycles by acquiring (or investing in) already established firms. The alternative is to start-up new ventures through extensive (and timeconsuming) R&D activities. It is hypothesised here that economic growth generates positive market sentiment about future economic states and the success of investment programmes, thus increasing the likelihood of observing M&A activity. The hypothesis is stated as follows.

> ***Hypothesis 19: Ceteris paribus, takeover probability will increase with the overall market performance.***

The hypothesis argues that the propensity for takeovers to occur is likely to increase with general stock market performance due to the positive effect market performance has on market sentiment. The performance of the FTSE All Share index in the preceding year is used to proxy for market-economics. Consistent with Bi and Gregory (2011) market performance in each year is computed as the 12-month (ending June 30th) return on the FTSE all share index. A year is defined as the period between 1 July year *t* and 30 June year *t*+1. This definition is informed by the portfolio formation strategy – the June approach – further discussed in chapter 4. A positive change in the performance of the FTSE All share from one year to another is expected to drive positive market sentiment and hence increase the propensity for takeovers to occur, and vice versa.

3.3.13 Summary

This study attempts to contribute to the takeover likelihood modelling literature by proposing, developing and incorporating several new hypotheses into the modelling framework. Eleven new takeover prediction hypotheses (including firm size, firm capital structure, financial distress, firm age, M&A rumours, payroll synergies, share repurchases, asymmetric valuation, industry concentration, market liquidity and market sentiment), have been proposed and discussed in this section (3.3). The hypotheses have been developed based on three different literatures: the neoclassical theory of mergers, the managerial (utility) theory of mergers and theories on merger waves. To the best of my knowledge, this is the first time these hypotheses will be used in the development of target prediction models.

3.4 Chapter summary and conclusion

Takeovers are complex investment decisions, arguably making them difficult to model. Some researchers have suggested that it is possible takeovers occur for a multitude of motives and therefore no single theory might fully explain the motives for takeovers. Roll (1986), for example, argues that his evidence on why takeovers are perpetrated ‘supports the hubris hypothesis as much as it supports other explanations such as taxes, synergy and inefficient target management’ (p. 197). This highlights the necessity to investigate a wide range of takeover motives in every prediction model.

This study builds on the contentions of Ambrose and Megginson (1992) and Powell (1997), who argue that the prediction hypotheses put forward by Palepu (1986) and recurrently used in the literature are, perhaps, insufficient to model takeovers. It contributes to the literature by proposing (and employing) eleven new prediction hypotheses in an attempt to improve takeover likelihood modelling. This new hypotheses also provokes new thinking on why firms engage in merger activity. The eleven new and six old hypotheses discussed in this chapter, as well as their predictions, are summarised in table 3.4.1 below. The evidence suggests that the motivations of mergers are dynamic in nature and are, perhaps, shaped by a multitude of factors (including firm specific and environmental), which may change over time and across different transactions. The set of 19 hypotheses is expected to more fully capture the dynamics on how firm characteristics moderates takeover likelihood.

Notwithstanding, this expansion of the set of predictive hypotheses presents new challenges in modelling. For example, an increase in the set of predictive variables reduces the degrees of freedom and increases the likelihood of encountering the problem of multicollinearity in regression analysis. These issues are discussed in the next chapter (4). Further, some of the hypotheses are likely to overlap – at least empirically. For example, other things remaining equal, higher leverage (capital structure hypothesis) generates lower free cash flow (free cash flow hypothesis) and a higher payroll cost (payroll synergies hypothesis) implies lower profitability (management inefficiency hypothesis). I review collinearity diagnostics (bivariate correlations and variance inflation factors) to ensure that these problems are not so severe so as to invalidate the findings. In chapter 5, I develop alternative models with different input variables in an attempt to assess the impact of the problem. In chapter 6, I also evaluate models without these variables and show that their inclusion in the model improves its predictive power. Chapter 4 focuses on the empirical methods used in testing the hypotheses and developing the takeover target prediction model. It also discusses the sample used in the study, the sources employed for data collection, the data collection process and the methodology used in chapters 5, 6 and 7.

Table 3.4.1 Summary of new and old hypotheses for takeover prediction

Hypothesis		Hypothesis statement (Ceteris paribus)	Expected sign
Panel A: Old hypotheses			
1	Inefficient management	The probability that a firm will become the subject of a takeover bid decreases as its performance increases	Performance: –
2	Undervaluation	Takeover probability increases with the level of firm undervaluation	Undervaluation: +
3	Industry disturbance	The likelihood of takeovers within an industry will increase with the announcement of a merger bid in that industry	Disturbance: +
4	Free cash flow	Takeover likelihood increases with a firm's level of free cash flow	Free cash flow: +
5	Growth-resource mismatch	Low-growth-resource-rich firms as well as high-growth-resource-poor firms have a high takeover likelihood	Mismatch: +
6	Tangible assets	Takeover probability increases with the proportion of tangible assets in a firm's total asset portfolio	Tangible assets: +
7	Firm size	Takeover probability decreases with firm size	Firm size: –
8	Firm age	Takeover probability decreases with firm age	Firm age: –
Panel B: New hypotheses			
9	Firm size	Takeover probability is an inverse U-shaped function of firm size i.e., takeover likelihood initially increases with size then declines as firm size exceeds a threshold	Firm Size: + Firm Size Squared: –
10	Firm capital structure	There is an inverse U-shaped relationship between a firm's leverage and the probability that it will receive a takeover bid.	Leverage: + Leverage squared: –
11a	Financial distress	Takeover likelihood increases with the level of financial distress. That is, takeover likelihood decreases with a firm's Z score	Zscore: +
11b		Firms with a high probability of going bankrupt (i.e., firms with Z scores below 0) will have a low takeover probability	Bankrupt: –
12	Firm age	Takeover probability is a U-shaped function of firm age i.e., takeover likelihood initially decreases with age then increases as firm age exceeds a threshold	Firm age: – Firm age squared: +
13	M&A rumours	A firm's takeover probability increases with the presence rumours about the firm becoming a prospective takeover target	Rumours: +
14	Payroll synergies	Takeover probability is an inverse U-shape function of payroll burden.	Payroll: + Payroll Squared: –
15a	Share repurchases	Takeover probability will decline when a firm engages in share repurchase activity.	Repurchase: –
15b		Takeover probability will increase when a firm engages in share repurchase activity	Repurchase:+
16	Asymmetric valuation	Takeover probability will decrease as the level of target information asymmetry increases	Residual Volatility: –
17	Industry concentration	Takeover probability will decrease as the concentration of a firm's industry increases.	Industry conc: –
18	Market liquidity	Takeover probability will increase with market liquidity	Mkt liquidity: +
19	Market sentiment	Takeover probability will increase with market performance	Market performance: +

Notes: All hypotheses are stated on a 'ceteris paribus' basis i.e., all other things being equal. The expected sign is the hypothesised relationship between takeover probability and the stated variable. Hypotheses 1to 8 are the old hypotheses and hypotheses 9-19 are the old hypotheses.

4.1 Overview

The chapter discusses the sample used as well as the methodology employed in the empirical analysis. With respect to the sample, it discusses the sample characteristics, the data collection process and the development of a database[124] which is appropriate for the modelling methodology. In terms of methodology, it discusses the applicability of the logit model (as base model for takeover prediction), methods for validating the old and new prediction hypotheses (discussed in chapter 3) and methods for testing the new model's performance (explanatory power and investment potential). This chapter is the basis of results presented in the next three chapters (i.e., chapters 5, 6 and 7)[125]. The construction of the sample, the collection of data and the development of the database is discussed in section 4.2. Section 4.3 discusses the methodology for hypotheses validation, section 4.4 discusses the methodology for testing the models' predictive ability and section 4.5 discusses the methodology for evaluating the models' ability to generate abnormal returns for investors.

4.2 Sample and data

4.2.1 Overview

Takeover target prediction modelling (as per this study) involves the development of models to predict firms that are likely to receive takeover bids in the next year based on their current characteristics as well as the environmental conditions. This section discusses the sample construction, data collection for the dependent and independent variables, data collation and database matching (to develop the prediction model database), as well as the procedure for identifying and eliminating outliers in the data.

[124] The task here is to manage the differences between different firm year ends, as well as, the differences between the time at which financial data is observed (annually) and market data is observed (continuously) when computing financial ratios.

[125] Chapter 5 focuses on testing the hypotheses developed in chapter 4. Chapter 6 focuses on evaluating the performance of this model in terms of distinguishing between targets and non-targets. Chapter 7 focuses on evaluating the model's ability to generate abnormal returns for investors.

4.2.2 Sample construction

The modelling methodology introduced by Palepu (1986) and widely used across the literature[126] has been criticised outside the takeover target prediction literature (e.g., in bankruptcy prediction modelling) for generating bias in regression coefficients (see, for example, Platt and Platt (2002) and Shumway (2001)). This is further discussed in section 2.6.3. Consistent with Cornett et al. (2011), Bhanot et al. (2010) and Cremers et al. (2009), a panel data sampling approach is used in this study. I start by identifying the sample of all firms (dead and live) that have been (or are) listed on the London Stock Exchange (main market) up until January 2011[127]. DataStream codes: FBRIT and DEADUK1–7, are used to generate a list of all UK live and dead firms respectively (together with their DataStream codes). The initial list of all live and dead UK firms is made up of 8,970 firms of which 1,929 firms are active, 7,001 firms are dead and 40 firms are suspended.

The 'inactive dates' for dead firms are also extracted from DataStream using the TIME data type. The dates (death month) provided by DataStream's TIME data type broadly correspond with the Death Month (M3) data type from the London Share Price Data (LSPD) database master index file. Observations with death dates prior to 1988 are excluded from the sample. This procedure eliminates 1,692 dead firms, reducing the number of dead firms to 5,309 and the total number of firms to 7,278. The sample of 7,278 firms is described as the initial sample on which preliminary financial data is gathered. Upon data collection, I find that a further 351 active firms, 2,953 dead firms and 3 suspended firms do not meet minimum data requirements of financial data on total assets and total revenues in at least one year and do not have DataStream industry classification or SIC codes[128]. Most of the 351 active firms are not listed as equities. A majority of the 2,953 dead firms, perhaps, were inactive before 1988[129].

Next, the sample of 3,971 firms is classified into 12 industry groupings. There is no standard method for industry classification in prior research. I employ a simple classification system based on the 2007 UK Standard Industry Classification (SIC 2007)

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126 See, for example, Barnes (1990, 1999), Ambrose and Megginson (1992), Walter (1994), Powell (1997), Espahbodi and Espahbodi (2003) and Brar et al. (2009), amongst others.

127 The coverage of financial data for this study is from 1988 to 2009 while the coverage of M&A data is June 1990 to June 2011. This is further discussed in sections 4.2.3 and 4.2.4.

128 A majority of proxies used in the study employ a denominator of total assets or total revenues in the computation of financial ratios.

129 I attempt to gather data for these firms and find that they have no financial data for the 1988–2009 period.

scheme. This scheme is similar to (but broader than) that employed in Renneboog and Trojanowski (2007) and consistent with that employed by DataStream. The industry groups are summarised in table 4.2.2.

Table 4.2.2: Sample characteristics and industry distribution

SIC code R	Industry groupings	Abbrev.	Active	Dead	Susp.	Total
0100 – 0999	Agriculture, Hunting & Forestry	AHFF	13	9	0	22
1000 –1499	Mining & Quarrying	MQ	222	16	3	241
1500 –3999	Manufacturing	MAN	420	799	9	1,228
4000 – 4499	Electricity, Gas & Water	EGW	25	33	0	58
4500 – 4999	Construction	CON	85	159	1	245
5000 – 5499	Wholesale & Retail	WRT	47	179	5	231
5500 – 5999	Hotels & Restaurants	HR	67	156	4	227
6000 – 6999	Financial Intermediation	FI	406	583	12	1,001
7000 – 7499	Real Estate & Business Services	RERB	240	378	5	623
7500 – 7999	Public admin. & Defence	PAD	52	112	1	165
8000 – 8499	Education & Training	EDU	15	39	0	54
8500 – 9999	Social work, Health & Other Services	SWH	78	127	0	205
	Total		1,578	2,356	37	3,971
Less	Financial intermediation	FI	406	583	12	1,001
Final Sample (Master List)			**1,172**	**1,773**	**25**	**2,970**
Insufficient data		NA	351	2,953	3	3,307
Initial Sample						**7,278**

Notes: This table presents the industry distribution of the sample. The SIC code R. is the range adopted to define industries using SIC codes. This classification (Industry groupings) builds on the recent UK SIC 2007 classification scheme, the classification scheme employed by Renneboog and Trojanowski (2007) as well as the industry definitions reported by DataStream. Active firms are firms which are listed on the stock exchange in January 2011. Dead firms are firms which were listed in January 1988 but not in January 2011. Suspended firms are firms whose stocks are no longer traded in the stock exchange but have not been official delisted. Firms in the financial intermediation (FI) sector are excluded from further analysis. The final sample used in the study is made up of 2,970 firms – 1,172 live, 1,773 dead and 25 suspended firms.

As in prior studies, financial intermediaries (SIC code 6000–6999) are excluded from the analysis as they are known to follow unique reporting standards which makes the interpretation of their financial ratios different from those of other firms (see, for example, Renneboog and (2007), Brar et al. (2009) and Ouzounis et al. (2009) for a discussion). The final sample used in this study is made up of 2,970 firms (with 1,172 active firms, 1,773 dead firms and 25 suspended firms). This sample of 2,970 firms constitutes the ‘master list’ on which accounting and market data is gathered. The data on the independent variables (i.e., proxies to the hypotheses) collected from DataStream (discussed in section 4.2.3) as well as the data for the dependent variable (takeover likelihood) collected from

OneBanker (discussed in section 4.2.4), are matched with the ‘master list’ using DataStream codes. The matching procedure – the June approach – is discussed in section 4.2.5.

4.2.3 The independent variable – hypotheses proxies

The independent (or explanatory) variables in the model include the nineteen hypotheses (eight old hypotheses and eleven new hypotheses) discussed in chapter 3. The proxies and constituent variables or DataStream data items for these hypotheses are also discussed in chapter 3. A summary is shown in table 4.2.3. As shown in the table, four main data types are required. These include: (1) firm accounting data (e.g., total assets, revenues, and total equity; obtainable from DataStream), (2) firm stock market data (e.g., share price and number of shares outstanding; obtainable from DataStream), (3) macroeconomic and market data (e.g., LIBOR, BOEBR and FTSE All-Share returns; obtainable from DataStream), and (4) M&A data (e.g., merger targets, merger rumours, and share repurchase announcements; obtainable from OneBanker).

The DataStream codes (see table 4.2.3) are used to obtain year-end financial data for each of the 2,970 firms on the master list (discussed in section 4.2.2) between January 1988 and December 2009. Every firm on the list contributes an observation to the dataset in every year or up to a point when it is delisted (e.g., due to bankruptcy or acquisition). Stock market data for each of the firms on the master list (including number of shares outstanding [NOSH] and share price [UP]) are collected from DataStream as at June 30th of each year between 30th June 1989 and 30th June 2010. The rationale for this choice is discussed in section 4.2.5. Daily adjusted share price [RI] data that includes dividend payments for each firm is also collected and used to compute daily stock returns (discussed in section 3.3.2). Information on share repurchases activity and merger rumours (including the announcement date, the firms involved and their DataStream codes) are collected from Thomson OneBanker. DataStream codes are used to match the data from OneBanker with the data from DataStream. The matching procedure is discussed in section 4.2.5. Monthly data for macroeconomic variables (LIBOR and BOEBR) and market variables (FTSE All-Share return) are collected from DataStream and corroborated with data obtained from the British Bankers Association’s (BBA) LIBOR database. These four types of required data (model explanatory variables) are collected and used to populate the master list to generate an unbalanced panel dataset of all explanatory variables. The unbalanced panel dataset is made up of 32,363 firm-year observations generated from 3,433 unique firms.

Table 4.2.3: Hypotheses, proxies and constituent DataStream variables

Hypotheses	Proxies (Exp. sign)	Constituent variables (DataStream codes)
Panel A: Old Hypotheses		
Inefficient Management	Profitability (–)	wc01250, wc03998
	ADAR (–)	RI (Firm and FTSE ALL Share index)
	LMDummy (+/–)	wc017151
Undervaluation	BTM (+)	wc03501, wc02649, NOSH, UP
	NBVDummy (+/–)	wc03501, wc02649, NOSH, UP
Industry Disturbance	IDummy (+)	SIC codes
Free Cash Flow	FCF (+)	wc04860, wc04601, wc02999
Growth-Resource Mismatch	Sales Growth (+/–)	wc01001
	Liquidity (+/–)	wc02001, wc02999
	Leverage (+/–)	wc03255, wc03995
	GRDummy (+)	wc01001, wc02001, wc02999, wc03255, wc03995
Tangible assets	PPP/TA (+)	wc02501, wc02999
Firm Size	Ln Assets (–)	wc02999
Firm Age	Age (–)	wc18273
Panel B: New Hypotheses		
Firm Size (new)	Ln Assets (+)	wc02999
	Ln Assets sq. (–)	wc02999
Firm lifecycle	Age (–)	wc18273
	Age sq. (+)	wc18273
Capital Structure	Leverage (+)	wc03255, wc03995
	leverage Sq. (–)	wc03255, wc03995
Financial Distress	Z Score (–) & ZSDummy (–)	wc01401, wc03101, wc02201, wc03255, wc01151, wc02201, wc02101
M&A Rumours	MRDummy (+)	OneBanker
Payroll Synergies	HR. Cost to sales (+)	wc01084, wc01001
	HR. Cost to sales Sq. (–)	wc01084, wc01001
Share Repurchases	SRDummy (+/–)	OneBanker
Asymmetric Valuation	Residual Volatility (–)	RI (Firm and FTSE ALL Share index)
Industry Concentration	Herfindahl Index (–)	wc01001
Market Liquidity	LIBOR-BOEBR (–)	LIBOR, BOE Base rate
Market Sentiment	FTSEChange (+)	FTSE All Share index

Notes: The table presents the constituent DataStream variables used to develop proxies for the hypotheses. The old and new hypotheses are presented in panels A and B, respectively. The proxies for these hypotheses, together with their expected signs, are shown in the second column. The computation of these proxies as well as variable definitions is discussed in chapter 3. Profitability is the ratio of EBITDA to total capital employed. LMDummy takes a value of 1 when a firm makes a loss and a value of 0 otherwise. ADAR is the average daily abnormal return. Book to market (BTM) is the ratio of book value of equity to market value of equity. NBVDummy takes a value of 1 when a firm's BTM is negative and a value of 0 otherwise. Sales growth is the rate of change in total revenues from the previous period. Liquidity is the ratio of cash and short term investments to total assets. Leverage is the firm's debt to equity ratio. GRDummy takes a value of 1 when there is a mismatch between a firm's growth opportunities and its resources and a value of 0 otherwise. IDummy takes a value of 1 if a takeover occurs in a firm's industry and a value of 0 otherwise. FCF/TA is the ratio of free cash flow (operating cash flow less capital investments) to total assets. PPE/TA is the ratio of tangible assets (property, plant and equipment) to total assets. Age is the number of years since incorporation. Ln Assets is the natural log of a firm's total assets. SRDummy takes a value of 1 if a firm announced any share repurchases in the period and a value of 0 otherwise. MRDummy takes a value of 1 if a firm is the target in a merger rumour and a value of 0 otherwise. ZScore is a firm's Taffler Z Score. ZSDummy takes a value of 1 if a firm has a negative Z Score and a value of 0 otherwise. HR Cost to sales is the ratio of payroll expenses to revenues. Herfindahl index is the concentration of the firm's industry in a particular year. Residual volatility is the standard deviation of a firm's abnormal return in the year to June 30th. FTSEChange is the performance of the FTSE All Share index in the year to June 30th. LIBOR-BOEBR is the spread between the LIBOR and the Bank of England's base rate. The hypothesised sign is shown in brackets (e.g., (+), (-)). Data for all variables with DataStream codes is obtained from the Thomson DataStream database, while data for variables designated as 'OneBanker' is obtained from the Thomson OneBanker database.

4.2.4 The dependent variable – takeover probability

Several announced bids do not result in completed deals as the bids are successfully defended by the target, blocked by regulators or eventually withdrawn by the bidder. Event studies focusing on announcement day return show that targets gain substantially when a merger bid is announced, irrespective of whether the bid is eventually successful or unsuccessful (see, for example, Samuelson and Rosenthal (1986)). Ruback (1988), nonetheless, shows that targets of failed bids lose over half of their announcement day return (of 31.0%) when the offer is eventually withdrawn. Even though it appears optimal (from an investment perspective) to predict targets of successful bids (as opposed to all targets), the evidence suggests that distinguishing between targets of successful bids and targets of failed bids without prior knowledge of the terms of the deal is an onerous task. Bartley and Boardman (1990), for example, argue that whether a bid is successful or fails is dependent on external factors (other than target financial characteristics). Walkling (1985) finds that the difference between failure and success in merger bids is explained by variables such as managerial resistance, competition in the bidding environment, bid or offer premium, solicitation activities by brokers and bidder's toehold, and not by firm financial characteristics. The loss of over 30.0% of the target's announcement returns upon merger termination (as shown in Ruback (1988)) indicates that, on the announcement day, even with full knowledge of the terms of the deal, the market is still only partially able to ascertain the likelihood that the deal will be completed.

The goal of this study is to develop a model to predict firms that are likely to receive takeover bids, irrespective of the final outcome (success or failure) of the bid. In line with prior studies (e.g., Ambrose and Megginson (1992), Cornett et al. (2011)) and the evidence discussed above, no distinction is made between targets of failed bids and targets of successful bids. Consistent with prior studies (Palepu (1986), Ambrose and Megginson (1992), Walter (1994), Powell (2001), Powell and Yawson (2007), Brar et al. (2009) and Cremers et al. (2009)) no distinction is made between hostile and friendly targets[130]. The key event date is the date when the initial bid is announced. Not all merger bids are considered. In line with prior studies (such as Cornett et al. (2011) and Ambrose and Megginson (1992)[131]), only bids that (if completed) will lead to a transfer of control rights are considered (i.e., the bidder aims to own more than 50.0% of the target). Data for 8,358 M&A announcements involving publicly listed UK targets between 1st June 1989 and 30th June 2011 is collected from OneBanker.

Of the 8,358 announcements, 2,071 announcements do not result in the acquisition of control rights (if the bidder is successful). 780 of the bids are described as rumours or intentions. Consistent with section 4.2.2, 1,837 announcements involving targets in the financial industry are also excluded from further analysis. Of the remaining announcements, 871 targets are excluded as no target DataStream codes are available on OneBanker. The final sample is made up of 2,799 acquisition bids for UK public targets made between 1st July 1989 and 30th June 2011. The sample construction process is summarised in table 4.2.4a below.

130 Besides the lack of strong evidence in support of the use of multinomial models which distinguish between hostile and friendly targets (see Powell (1997, 2004)), the number of hostile targets in the population is perhaps too few to allow for any meaningful analysis.

131 Ambrose and Megginson (1992) defined a takeover bid as 'an announced attempt to accumulate or acquire majority voting power (50.1% or more of the outstanding voting shares) of another firm (p. 577). A bid in which a bidder increases its stake in the target from 20% to 51%, for example, is considered as a takeover bid. A bid in which a bidder increases his stake from 60% to 90% is not considered given that there is no acquisition of control through such a takeover.

Table 4.2.4a: M&A data collection and sample construction

All bids	8,358
Bids for minority stakes	2,071
Rumours and intensions	780
Financial intermediaries	1,837
No DataStream Code	871
Number of bid announcements	2,799

Notes: The table shows the process of streamlining the initial dataset of 8,358 M&A bid announcements recorded in Thomson OneBanker (between July 1st 1989 and June 30th 2011) to the final sample of 2,799 useful (control) bids. The final sample is obtained by excluding bids which do not meet conceptual and data requirements. That is, bids which do not result in an acquisition of control rights, bids which are classified as 'rumours' or 'intensions' and bids involving financial intermediaries, are excluded from all bids. Cases without DataStream codes are excluded as these codes are needed to match the data from the two databases. Of the 8,358 announcements, 2,071 announcements do not result in the acquisition of control rights (if the bidder is successful). 780 of the bids are described as rumours or intentions. 1,837 announcements involving targets in the financial industry are excluded from further analysis. 871 targets are excluded as no target DataStream codes are available on OneBanker. The final sample is made up of 2,799 acquisition bids for UK public targets made between 1st July 1989 and 30th June 2011.

As shown in table 4.2.4b, a majority (66.92%) of the 2,799 M&A cases are successful and lead to a transfer of control rights from the target to the bidder. The average transaction value of the 1,873 successful merger bids (or control contests) is over £586.76 million[132]. On average, the bidder holds about 95.73% of the target when the acquisition is completed.

Table 4.2.4b: Characteristics of the sample of bid announcements

Classification	Number (%) of targets		Average transaction value (£millions)	Bidder post-acquisition average holding (%)
Completed	1,873	66.92%	586.76	95.73
Part Comp	1	0.04%	–	–
Pending	117	4.18%	87.76	–
Status Unknown	102	3.64%	32.14	–
Unconditional	199	7.11%	143.62	29.45
Withdrawn	507	18.11%	1,629.75	17.16
Total (Average)	2,799	100.00%	(669.02)	(89.87)

Notes: The table shows the classification of the different bids that make up the sample. A substantial proportion of bids in the sample (66.92%) are successful bids which lead to the acquisition of control rights by the bidder. 507 withdrawn bids indicate bids that can be considered as failed bids. The status of 219 bids (pending and unknown), i.e., whether such bids are eventually completed or withdrawn, is not clear. These bids are not excluded in the sample as any risk of double counting is averted by the matching methodology employed in section 4.3.5. The average transaction value of failed deals is £1,629.75 million, which is substantially higher than the average transaction value of successful bids (£586.76 million). The bidder's post-acquisition holding in failed bids is 17.16% on average i.e., below the 50% threshold required for control.

132 The transaction value of £586.76m is the average for 1,456 deals. Transaction value for 417 successful deals is not reported in OneBanker.

The results in table 4.2.4b indicate that 18.11% of the bids are eventually withdrawn (or fail). The average transaction value of these failed deals is £1,629.75 million, which is substantially higher than the average transaction value of successful bids (£586.76 million). The bidder's post-acquisition holding in failed bids is 17.16% on average i.e., below the 50% threshold, as expected.

OneBanker does not distinguish between initial bid announcements and subsequent bid revisions. The implication is that the sample of 2,799 might also contain bid revisions (for the same target by the same bidder) and multiple bids (for the same target by different bidders) during the same time period. Indeed, I find that the list of 2,799 bids sometimes registers different phases of the bid process (e.g., initial announcement, bid revision, bid completion or withdrawal) as distinct bids. It is also possible that a single target receives several independent bids at different points within the same year. The algorithm for developing the database (discussed in section 4.3.5) prevents double counting by restricting each firm to a maximum of one bid within a one year period[133]. Variables such as the identity of the bidder(s) and the number of bidders are irrelevant to the analysis.

The dependent variable $P(i,t)$ is a binary variable, defined as the probability that firm i will receive a takeover bid in the period t. Each of the 2,799 'targets' are assigned a takeover probability of 1 in the year in which they receive a takeover bid. These 2,799 'targets' are matched to the firms on the 'master list' (discussed in 4.2.5 below). The result is a successful match of 1,635 firms[134]. All other firms on the master list (excluding the 1,635 targets) are assigned a probability of 0 for every year in which no bid is observed.

4.2.5 The procedure for database development

As discussed in section 4.4.3, much of the empirical analysis in this study relies on results obtained from back-testing. Although this is the standard methodology employed in the literature, it frequently leads to look-ahead bias. The algorithm for data mapping aims to minimise any look-ahead bias in back-tests by reflecting the data-related challenges faced by investors and other users of the model in real life. As will be discussed in section 4.3.3, the prediction model postulates that the takeover likelihood of a firm i at time t, denoted by $P(i,t)$, is a function of a vector of its characteristics at time t-1. The implication is that a

133 The earliest M&A event (i.e., initial bid announcement) is used as the M&A announcement date.
134 The implication is that the 2,799 recorded bids for control were for 1,635 unique targets. 1,030 recorded bid activity remain unmatched as they, perhaps, constitute multiple bids, bid revisions and bids within the same year. The rest of the bids (134) pertain to firms in the financial industries (FI).

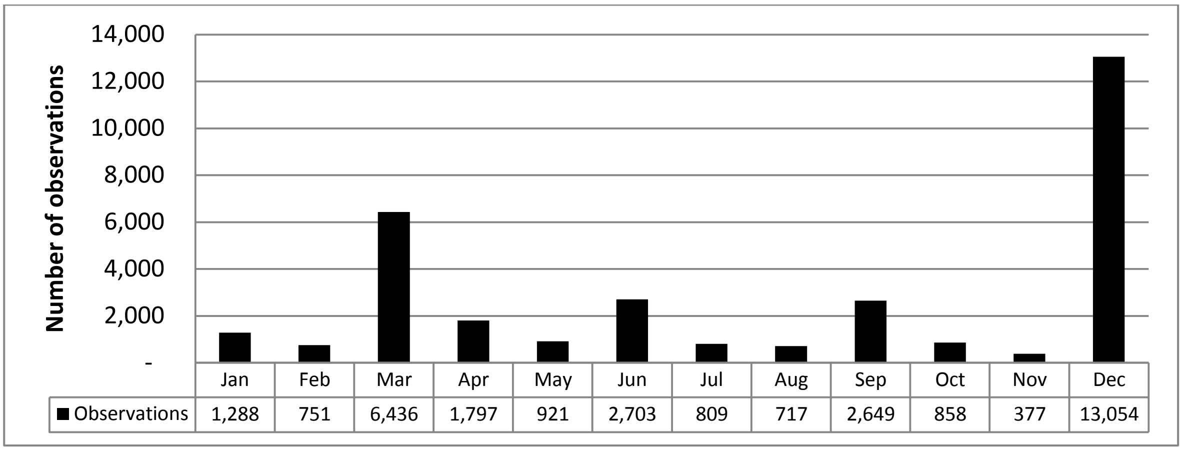
firm's characteristics in the current period determine its takeover likelihood in the next period. Data therefore needs to be appropriately lagged to make the modelling exercise realistic and free from bias.

The dependent variable (1,635 bid announcements obtained from Thomson OneBanker) is matched with the independent variables (unbalanced panel dataset of 32,363 firm-year observations) on this basis. The matching process is further complicated by two issues: (1) the fact that all firms do not generally share a similar financial year-end (or balance sheet date), and (2) the observation that firm financial data is not typically publicly available on the balance sheet date[135]. This issue is further discussed in section 2.6.3. In the UK, the Companies Act allows public firms to file their reports to the Companies House up to six months after the reporting year-end[136].

The 'June approach' to lagging UK financial data for forecasting purposes (as discussed in Soares and Stark (2009)) is tailored and adopted in this study. This approach builds on Fama and French (1993) who apply a portfolio inception date of July 1st. In this context, the approach assumes that takeover prediction models are developed on June 30th (of each year) and used to predict and invest in targets from July 1st. This approach is based on the observation that a significant proportion of UK firms have a December year-end and the fact that the regulation allows public firms to publish their financial results within six months of their financial year-end (Soares and Stark (2009)). In support of Soares and Stark (2009), I find that over 40.34% of the observations in my sample have a December year-end (and about 19.89% of the observations have a March year-end). The distribution of firm-year ends for the firm-year observations in my sample is shown in the chart below.

[135] Although data is available as at balance sheet date in back-tests, the use of such data constitutes look-ahead bias, as the data is only made available to the public (sometimes up to six months) post balance sheet date.
[136] Before the 6th April 2008, the UK Companies Act allowed firms to file their reports up to 7 months after year end.

Figure 4.2.5a: The distribution of firm year-ends for firms in the sample



Note: The chart presents a summary of the financial year-ends of the 35,363 firm-years in the sample. Firm-years are used (as opposed to firms) as a balanced sample is not employed in the analyses and a number of firms change their financial year-end over the period. The X axis represents the calendar month of the financial year-end. The Y axis represents the number of firm-year observations for each calendar month of the financial year-end. The results show that a majority (40.34%) of observations (firm-years) in my sample have a financial year-end which coincides with the calendar month of December. About 19.89% of the firms in the sample have a March year-end.

The results in figure 4.2.5a suggest that a substantial proportion of firms publish their financial results between January and June of each year (i.e., a large proportion of firms have a December year-end). This is further discussed below. The June approach simplifies the modelling process by assuming that all firms have their data available (to the public) on the June 30th of each year (e.g., 30 June 2010) for the financial year-ending sometime during the previous calendar year (e.g., 1 January 2009 – 31 December 2009). Clearly, some firms will publish their results a few months before this cut-off (June 30th). However, on average, June 30th, perhaps, represents the appropriate cut-off applicable for a large proportion of UK firms. If June 30th (of year 2010, for example) is assumed as the reference point when data is made available to the public, then, perhaps, all takeover activity between July 1st (year 2010) and June 30th (year 2011) can be attributed to June 30th (year 2010) data release.

Figure 4.2.5b: The June approach to database matching and proxy computation

Year	***t-1***												***t***												***t+1***					
Month	J	F	M	A	M	J	J	A	S	O	N	D	J	F	M	A	M	J	J	A	S	O	N	D	J	F	M	A	M	J
Firm financial year-end	*	*	*	*	*	*	*	*	*	*	*	*																		
Returns period							"	"	"	"	"	"	"	"	"	"	"	"												
Bid announcement date																			X	X	X	X	X	X	X	X	X	X	X	X
Bid announcement date	**X**	This is the month in which a bid is announced as indicated by OneBanker																												
Firm financial year-end	*	This is the balance sheet date, i.e., the month up until which financial statements are prepared.																												
Returns period	"	Daily returns and residual volatility are computed using data from July year t-1 to June year t																												

Notes: This figure demonstrates the application of the June approach in this study. The letters, JFMAMJJASOND in row 2, represent all calendar months from January (J) to December (D) respectively. *t-1, t* and *t+1* in row 1, represent three sequential calendar years. The table shows how a database holding key prediction variables, as well as the dependent variable is constructed (by matching data from different sources (DataStream and OneBanker), using the 'June approach' discussed in Soares and Stark (2009). For each firm on the master list (of dead and live firms), I identify the financial year-end (*). The month of the financial year-end (*) can be any month from January year *t-1* to December year *t-1*. Most firms have a December year-end so a cut-off of December year *t-1* is assumed (see figure 4.2.5a). To allow for the firm's financial data to be available to the public, a 6-month gap is given. It is assumed that each firm's financial data is available by the 30 June year *t* (6 months after December year *t-1*). That is, for any firm with financial year-end between January year *t-1* and December year *t-1*, I assume its data is publicly available on the 30 June year *t*. It is assumed that the prediction model is developed when data is available to the public (i.e., 30th June year *t*). I therefore match market data on June 30th year *t* to financial data for year-end January year *t-1* to December year *t-1*. I assume that any merger bid (X) tendered by bidders between 1 July year *t* and June year *t+1*, relies on data available to the bidders on June 30th year *t* pertaining to the financial year January year *t-1* to December year *t-1*. I compute 1-year market performance (ADAR – management inefficiency hypothesis) and residual volatility (Asymmetric Valuation hypothesis) using daily data between July year *t-1* and June year *t* ("). For the computation of ratios (such as book to market), I use stock price at June 30th year *t* and match this with financial data for year-end January year *t-1* to December year *t-1.*

Figure 4.2.5b illustrates the June approach for matching the event with firm characteristics and for computing market returns. As shown in the figure, for each firm on the master list, I identify the financial year-end. As shown in table 4.2.5a, over 40.34% of firms in my sample have a December year-end so a cut-off of December (e.g., December 2009) is assumed. As discussed above, the current UK regulation allows firms to publish their results up to six months after year-end. To allow for the firm's financial data to be available to the public, a 6-month gap is given. It is assumed that each firm's financial data is available by the 30th of June in the next calendar year (e.g., 30th June 2010, six months after December 2009). It is assumed that the prediction model is developed when data is available to the public (i.e., 30th June 2010) and the portfolio generated from this model is held for one year starting from 1st July 2010. In the example above, I therefore match market data on 30th June 2010 to accounting data for financial year-end January 2009 to December 2009. I assume that any merger bid tendered between 1st July 2010 and 30th June 2011 relies on data available to the bidders on 30th June 2010 pertaining to the financial year-end 2009. Hence, I match M&A data for period 1st July 2010 and 30th June 2011 to market data at 30th June 2010 and financial data for year-end 2009.

The computation of ratios which utilise market data (such as book to market ratio) matches June 30th market data with accounting statement data, assumed to be available by June 30th of the following calendar year (2010). For example, for calendar year end 2009, I compute 1-year market performance (ADAR – management inefficiency hypothesis) and residual volatility (Asymmetric valuation hypothesis) using daily data between July 2009 and June 2010. For the computation of ratios (such as book to market), I use stock price at 30th June 2010 and match this with data for financial year-end 2009. Each firm's book to market ratio in 2009 is computed as the ratio of its book value (at balance sheet date in 2009) to its market value on 30th June 2010.

Aside from eliminating look-ahead bias, the June approach is advantageous (from an investment perspective) as its implementation occurs only once each year thus resulting in low transaction costs (Soares and Stark (2009)). Soares and Stark (2009), however, note that a significant lag can arise implying that the approach will not always reflect data employed by the market. This will result in a negative bias and a likely underperformance of the empirical model.

It is worth noting that other approaches (like the September approach) have been used in studies such as Agarwal and Taffler (2008) and Gregory et al. (2013). This follows their finding that about 37% of UK firms have a December year-end as compared to 22% with a March year-end. These studies adopt an approach (September approach) which assumes that most firms have a financial year-end before March. Allowing 6 months for the publication of financial results, these studies match market data from September to financial data from March. While this approach is justified on the basis that it mitigates look-ahead bias, it can, potentially, lead to the over-reliance on stale data for takeover prediction in the current study. This is because I find that, in comparison to Gregory et al. (2013), a higher (lower) proportion of firms in my sample have a December (March) financial year-end. In my sample, 40.34 % (19.89%) of firms have December (March) year-end. Nevertheless, adopting the September approach rather than the June approach may be a further extension of this study.

The outcome of this data matching process is the expansion of the 'master list' into a panel database which holds firm information (computed proxies for old and new hypotheses) as well as the probability of a firm receiving a bid based on its characteristics at time *t* (modelled as a binary variable, as discussed in section 4.2.4). This unique database is then used to test the hypotheses and to develop the new prediction model. Prior to such tests, the database is scrutinised in a bid to identify and remove extreme values or outliers. The characteristics of the database as well as the outlier management process are further discussed in section 4.2.6.

4.2.6 Sample characteristics and dealing with outliers

As discussed in section 4.2.4, the final sample is made up of 32,363 firm-year observations drawn from a time period of 22 years (1988 to 2009). DataStream codes are used to match both databases (OneBanker and DataStream) using the approach discussed in 4.2.5. Some of the 3,433 firms (32,363 firm-year observations) do receive a takeover bid within a specific year and these firms are described as targets in that year. All firms for which no announcements were made are considered as non-targets (further discussed in section 4.2.4). Out of the 32,363 observations, 1,638 takeover bids (targets) are recorded leaving a sample of 30,725 non-targets firm-year observations. In terms of overall sample size, this sample compares favourably against the sample employed in prior UK studies (including

Powell (1997, 2001, 2004), Barnes (1990, 1998, 1999) and Ouzounis et al. (2009)). The samples used in these prior studies are discussed in section 2.5 (chapter 2).[137]

Table 4.2.6a shows the distribution of targets from one year to another over the sample period (1988–2009). The data shows that out of an average of 1,471 listed firms per year, 74 firms receive a bid (on average) in each year. The implication is that on average 5.05% of listed firms receive a bid each year. This level of takeover activity is similar to the 5.00% (between 1986 and 1995) reported by Powell (2004). This ratio varies from one year to another with a high of 9.80% in 1997 and a low of 2.55% in 1993. The lowest number of takeover bids made is recorded in 1993 with just 32 firms out of a population of 1,254 active firms, receiving a takeover bid. Highs of 160 and 151 bids are, respectively, recorded in 1997 and 1998, marking a peak in takeover activity in the UK.

Table 4.2.6a: Constitution of the panel dataset

FYE	Targets	Total Obs.	Prop. %	FYE	Targets	Total Obs.	Prop. %
1988	42	1,127	3.73%	1999	81	1,473	5.50%
1989	39	1,211	3.22%	2000	65	1,503	4.32%
1990	43	1,259	3.42%	2001	84	1,555	5.40%
1991	42	1,272	3.30%	2002	69	1,617	4.27%
1992	35	1,245	2.81%	2003	78	1,696	4.60%
1993	32	1,254	2.55%	2004	101	1,772	5.70%
1994	44	1,277	3.45%	2005	106	1,808	5.86%
1995	53	1,270	4.17%	2006	106	1,774	5.98%
1996	101	1,557	6.49%	2007	71	1,663	4.27%
1997	160	1,633	9.80%	2008	79	1,500	5.27%
1998	151	1,544	9.78%	2009	53	1,353	3.92%

Notes: The table shows the constitution of the dataset (in terms of number of unique firms and number of targets) and the proportion of targets from one year to another across the 22-year period. FYE refers to the financial year-end of the accounting data to which the bids are matched. The June approach discussed in section 4.2.5 is used to match the announced bids to the relevant financial data. For example, bids pertaining to FYE 1988 occur (i.e., bid announcement date) between July 1989 and June 1990. The total number of targets (observation) is 1,638 (32,363). Prop. % is the ratio of targets to total firm year observations in each period. Out of an average of 1,471 listed firms per year, 74 firms receive a bid (on average) in each year. The implication is that on average 5.05% of listed firms receive a bid each year.

The descriptive statistics relating to the key financial variables for the sample are presented in table 4.2.6b. Table 4.2.6b presents descriptive statistics for proxies of management

137 For example, Palepu (1986) employs a US sample consisting of 163 targets and 256 non-targets. Powell (1997, 2001) employs a UK sample consisting of 411 targets and 532 non- targets. Powell (2004) which, to the best of my knowledge, is the most extensive UK study in takeover prediction to date, uses a panel sample consisting of 9,891 firm-year observations.

inefficiency, firm undervaluation and growth-resource mismatch hypotheses, economic disturbance, firm size, free cash flow, tangible assets, firm age, financial distress hypotheses, payroll synergies and asymmetric valuation. Other variables not shown in the tables (such as dummies and macroeconomic variables) are not treated for outliers. A full discussion and analysis of descriptive statistics of all variables is completed in chapter 5. The definitions and derivation of the variables are discussed in sections 3.3 and 3.4.

In panel A (table 4.2.6b), the descriptive statistics for the raw data is presented. As will be discussed, a key observation from panel A is the presence of extreme and, seemingly, implausible values. Some analysis on why such extreme values are observed is conducted and the results are presented in table 4.2.6c, 4.2.6d and 4.2.6e. In general, I find that the extreme values are not primarily due to database (DataStream) errors as original annual reports obtained from Perfect Information database corroborates the data obtained from DataStream. This is further discussed below.

In panel B, the raw data used in panel A is winsorised at the 1^{st} and 99^{th} percentile. That is values below the 1^{st} percentile are replaced with the 1^{st} percentile and values above the 99^{th} percentile are replaced with the 99^{th} percentile. As noted above, the focus is on firm specific data. All dummy variables (such as LMDummy, NBVDummy, GRDummy, IDummy, SRDummy, MRDummy), industry variables (Herfindahl index) and market variables (such as FTSEChange and LIBOR-BORBR) are excluded from the winsorisation process[138]. Firm size (natural log of total assets) and firm age (number of years since incorporation) are also not winsorised as no apparent extreme values are observed. As will be discussed below, the results from panel B shows an improvement from panel A but still suggests that more extensive winsorisation (in line with Christidis and Gregory (2010)) might be necessary. The effect of adopting a more extensive winsorisation procedure is investigated in section 5.4.

In panel C, the data in panel A is now winsorised at the 5^{th} percentile and the 95^{th} percentile (in line with Christidis and Gregory (2010)). As will be discussed below, this procedure leads to an improvement in the variables' distribution, with no apparent extreme values. The data used in panel C – data winsorised at the 5^{th} and 95^{th} percentile – is adopted for all further analysis (chapters 5, 6 and 7).

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[138] See table 4.2.3 for full variable definitions.

Table 4.2.6b Descriptive statistics and treatment of outliers

Panel A: Raw Data

Hypothesis	Proxies	N Valid	N Missing	Mean	Median	Std. Dev	Skew	Min	Max	Percentiles 25	Percentiles 75
Inefficient Management	ADAR	25,406	6,959	0.0001	0.0002	0.0021	1.8621	-0.0154	0.0674	-0.0009	0.0011
	Profitability	32,363	2	0.0402	0.1178	1.4949	-5.4792	-36.3200	34.2727	0.0000	0.2309
Undervaluation	Book to Market	27,586	4,779	0.5337	0.3722	2.6101	17.4675	-37.5242	98.5250	0.1231	0.7501
Growth Resource Mismatch	Sales Growth	28,459	3,906	0.3322	0.0892	1.6086	11.7003	-1.0000	37.2647	-0.0257	0.2600
	Liquidity	32,343	22	0.1572	0.0808	0.2021	2.0621	0.0000	1.0000	0.0230	0.2020
	Leverage	32,348	17	0.5254	0.2690	3.2324	5.2654	-52.9412	73.2500	0.0182	0.6551
Firm Size	Ln Assets	32,354	11	17.7070	17.5259	2.2540	0.2059	6.9078	25.9761	16.2580	19.0033
Free Cash Flow	FCF/TA	25,160	7,205	-0.0755	0.0090	0.7005	24.8093	-14.5310	50.0975	-0.0856	0.0714
Tangible property	PPE/TA	32,105	260	0.3127	0.2659	0.2537	0.7589	0.0000	1.0000	0.0943	0.4620
Firm Age	Age	29,886	2,479	31.8159	17.0000	32.5718	1.0556	0.0000	164.0000	6.0000	54.0000
Financial Distress	ZSCORE	27,336	5,029	53.6836	8.0553	246.9343	8.5348	-992.0700	3,809.6884	2.0281	19.7469
Payroll Synergies	Salaries/Sales	23,572	8,793	0.5734	0.2638	2.1053	11.6487	0.0000	43.0625	0.1650	0.4007
Asymmetric Val.	Res. Volatility	25,406	6,959	0.0250	0.0196	0.0210	11.6445	0.0000	1.2330	0.0129	0.0307

Notes to panel A: This table presents the descriptive statistics of the key variables in the dataset prior to winsorisation. The first and second columns show the hypotheses and associated proxies. ADAR is the average daily abnormal return, profitability is the ratio of EBITDA to total capital employed, book to market is the ratio of book value of equity to market value of equity, sales growth is the rate of change in total revenues from the previous period, liquidity is the ratio of cash and short term investments to total assets, leverage is the firm's debt to equity ratio, Ln Assets is the natural log of the firm's total assets, FCF/TA is the ratio of free cash flow (operating cash flow less capital investments) to total assets, PPE/TA is the ratio of tangible assets (property, plant and equipment) to total assets, Age is the number of years since incorporation, ZSCORE is the firm's Taffler Z score. Salaries/sales represent the payroll costs to sales ratio. Res. Volatility is residual volatility computed from the firm's one-year daily abnormal returns. The third and fourth columns show the number of observations and the number of missing observations.

Table 4.2.6b Descriptive statistics and treatment of outliers

Panel B: The effect of winsorising at 1% and 99%

		N		**Mean**	**Median**	**Std. Dev**	**Skew**	**Min**	**Max**	**Percentiles**	
Hypothesis	Proxies	Valid	Missing							25	75
Inefficient Management	ADAR	25,406	6,959	0.0001	0.0002	0.0019	-0.2837	-0.0060	0.0056	-0.0009	0.0011
	Profitability	32,363	2	0.0592	0.1178	0.6302	-2.2684	-3.6600	2.4445	0.0000	0.2312
Undervaluation	Book to Market	27,586	4,779	0.5023	0.3723	0.9885	1.2762	-3.3748	5.5782	0.1228	0.7513
Growth Resource Mismatch	Sales Growth	28,459	3,906	0.2988	0.0895	1.0393	5.4045	-0.8761	7.9277	-0.0253	0.2627
	Liquidity	32,343	22	0.1568	0.0808	0.2005	2.0206	0.0000	0.9298	0.0230	0.2020
	Leverage	32,348	17	0.4922	0.2690	1.4571	2.1994	-5.3014	9.1809	0.0180	0.6563
Firm Size	Ln Assets	32,354	11	17.7070	17.5259	2.2540	0.2059	6.9078	25.9761	16.2580	19.0033
Free Cash Flow	FCF/TA	25,160	7,205	-0.0677	0.0089	0.3168	-3.7483	-2.0207	0.3343	-0.0859	0.0714
Tangible property	PPE/TA	32,105	260	0.3125	0.2659	0.2532	0.7513	0.0000	0.9366	0.0943	0.4620
Firm Age	Age	29,886	2,479	31.8159	17.0000	32.5718	1.0556	0.0000	164.0000	6.0000	54.0000
Financial Distress	ZSCORE	27,336	5,029	72.7021	8.1606	319.1029	6.6223	-63.4318	2623.1001	2.0795	20.3357
Payroll Synergies	Salaries/Sales	23,572	8,793	0.5540	0.2644	1.5021	6.8299	0.0311	12.8240	0.1654	0.4032
Asymmetric Val.	Res. Volatility	25,406	6,959	0.0246	0.0196	0.0169	1.7809	0.0000	0.0947	0.0129	0.0307

Notes to panel B: This table presents the descriptive statistics of the key variables in the dataset when the variables are winsorised at the 1st and 99th percentiles. The first and second columns show the hypotheses and associated proxies. ADAR is the average daily abnormal return, profitability is the ratio of EBITDA to total capital employed, book to market is the ratio of book value of equity to market value of equity, sales growth is the rate of change in total revenues from the previous period, liquidity is the ratio of cash and short term investments to total assets, leverage is the firm's debt to equity ratio, Ln Assets is the natural log of the firm's total assets, FCF/TA is the ratio of free cash flow (operating cash flow less capital investments) to total assets, PPE/TA is the ratio of tangible assets (property, plant and equipment) to total assets, ZSCORE is the firm's Taffler Z score, Age is the number of years since incorporation. Salaries/sales represent the payroll costs to sales ratio. Res. Volatility is residual volatility computed from the firm's one-year daily abnormal returns. Firm size (natural log of total assets) and firm age (number of years since incorporation) are also not winsorised as no apparent extreme values are observed. The third and fourth columns show the number of observations and the number of missing observations.

Table 4.2.6b Descriptive statistics and treatment of outliers

Panel C: The effect of winsorising at 5% and 95%

		N		**Mean**	**Median**	**Std. Dev**	**Skew**	**Min**	**Max**	**Percentiles**	
Hypothesis	Proxies	Valid	Missing							25	75
Inefficient Management	ADAR	25,406	6,959	0.0000	0.0001	0.0026	0.7370	-0.0348	0.0600	-0.0012	0.0013
	Profitability	32,363	2	0.0852	0.1178	0.2839	-0.8665	-0.6534	0.5979	0.0000	0.2312
Undervaluation	Book to Market	27,586	4,779	0.4918	0.3723	0.5793	0.9027	-0.4400	1.9864	0.1228	0.7513
	Book to Market (P)	27,586	4,779	0.5288	0.3722	0.5333	1.2920	0.0000	1.9864	0.1228	0.7513
Growth Resource Mismatch	Sales Growth	28,459	3,906	0.1826	0.0895	0.3933	1.6020	-0.3859	1.3788	-0.0253	0.2628
	Liquidity	32,343	22	0.1494	0.0808	0.1766	1.5805	0.0003	0.6557	0.0230	0.2020
	Leverage	32,348	17	0.4941	0.2691	0.6560	1.9769	0.0000	2.6894	0.0180	0.6563
Firm Size	Ln Assets	32,354	11	17.7070	17.5260	2.2540	0.2059	6.9078	25.9761	16.2579	19.0035
Free Cash Flow	FCF/TA	25,160	7,205	-0.0396	0.0089	0.1821	-1.4865	-0.5528	0.1868	-0.0860	0.0714
Tangible property	PPP/TA	32,105	260	0.3109	0.2659	0.2492	0.6969	0.0023	0.8632	0.0943	0.4620
Firm Age	Age	29,886	2,479	31.8159	17.0000	32.5723	1.0556	0.0000	164.0000	6.0000	54.0000
Financial Distress	ZSCORE	27,336	5,029	29.6983	8.1606	66.2460	2.8682	-17.5933	273.9258	2.0790	20.3401
Payroll Synergies	Salaries/Sales	23,572	8,793	0.3393	0.2644	0.2687	1.7911	0.0571	1.1658	0.1653	0.4032
Asymmetric Val.	Res. Volatility	25,406	6,959	0.0171	0.0133	0.0169	4.4060	0.0000	0.5638	0.0061	0.0229

Notes to panel C: This table presents the descriptive statistics of the key variables in the dataset when the variables are winsorised at the 5th and 95th percentiles. The first and second columns show the hypotheses and associated proxies. ADAR is the average daily abnormal return, profitability is the ratio of EBITDA to total capital employed, book to market is the ratio of book value of equity to market value of equity, book to market (p) is the ratio of book value of equity to market value of equity when BTM is winsorised at the 0% and 95%, sales growth is the rate of change in total revenues from the previous period, liquidity is the ratio of cash and short term investments to total assets, leverage is the firm's debt to equity ratio, Ln Assets is the natural log of the firm's total assets, FCF/TA is the ratio of free cash flow (operating cash flow less capital investments) to total assets, PPP/TA is the ratio of tangible assets (property, plant and equipment) to total assets, ZSCORE is the firm's Taffler Z score, Age is the number of years since incorporation. Salaries/sales represent the payroll costs to sales ratio. Res. Volatility is residual volatility computed from the firm's one-year daily abnormal returns. Firm size (natural log of total assets) and firm age (number of years since incorporation) are also not winsorised as no apparent extreme values are observed. The third and fourth columns show the number of observations and the number of missing observations.

In table 4.2.6b, I consider different outlier treatment procedures given the presence of extreme values in my dataset. There are several extreme or implausible values in the raw data (panel A) as evidenced by the skewness statistics, the minimum and maximum values and the mean and median values. The skewness statistic for measures of profitability, book to market, sales growth, leverage, free cash flow, financial distress, payroll synergies and residual volatility are all substantially above the 3 threshold. While this measures whether the data is normally distributed, it also indicates the presence of extreme values. The large difference between the mean and median values (e.g., for Z score and sales growth), the very low (high) minimum (maximum) values, and the spread between the maximum and minimum values (e.g., for the book to market, profitability and leverage ratios) are further indications of the existence of extreme and/or implausible values.

These results (table 4.2.6b) raise some questions about data integrity and the suitability of DataStream as a source of data for the current research. I attempt to evaluate data integrity by manually checking a sample of observations. Here, I compare the data obtained from DataStream to the data in original annual reports obtained from the Perfect Information database. The main variables with, potentially, extreme observations are profitability, book to market ratios, sales growth, leverage, free cash flow and financial distress (as can be seen from table 4.2.6b). Financial distress (measured by Taffler Z score) is nonetheless, the outcome of several constituent variables, and, hence, the reasons behind extreme Z score observations are likely to be multiple. After a review, I find that the ‘problem’ variables generating the extreme values are earnings before interest, tax, depreciation and amortisation (EBITDA), total revenue and total shareholder equity. That is some firms report negative EBITDA, zero total revenues and negative shareholder equity in some years.

The approach I adopt for this review process involves identifying a sample of firms with the highest (20 firms) and lowest values (20 firms) for each ‘problem’ variable. I then obtain the firms’ original annual reports from Perfect Information database and compare the data from DataStream to the data presented in the reports. I conclude that the values are extreme (not implausible) if the data from both databases is the same.

The extreme observations for profitability (EBITDA to total capital employed) are due to negative reported earnings (EBITDA) for some firms and negative or low capital employed (due to negative or low shareholder equity) for others. The table below shows the values for EBITDA and capital employed obtained from original financial statements.

Table 4.2.6c: Comparing earnings (EBITDA) data from DataStream to data from source documents

Company	Year	EBITDA (£million)	Capital Employed (£million)	Profitability ratio (EBITDA/Capital Employed)	Ratio computed using DataStream Information
Panel A: Firms with extreme negative profitability					
SocialGo Plc	2009	-1.663	0.048	-34.64	-34.64
Business Control Solutions Group PLC	2002	-1.816	0.050	-36.32	-36.32
Birmingham City PLC	1998	1.167	-0.082	-14.23	-34.62
Xn Checkout Holdings	2002	-4.606	0.180	-25.59	-25.59
Intelligent Environments Group PLC	2001	-5.575	0.228	-24.45	-24.45
Panel B: Firms with extreme positive profitability					
Act Group PLC	1994	24.159	1.065	22.26	22.26
Michael Page	2000	73.352	3.901	18.80	18.80
Chalkwell Investments	2005	0.084	0.005	16.80	16.80
Anglo United PLC	1991	36.162	2.442	14.80	14.80
EG Solutions PLC	2005	0.101	0.008	12.63	12.63

Notes: The table compares earnings (EBITDA – earnings before interest, tax, depreciation and amortisation) data from DataStream to data obtained from source documents (annual reports) available from Perfect Information for a sample of firms with extreme values. The ratios (results) are presented in decimals. I manually check the data for several other firms but do not report these results for simplicity. Generally, I find that for the sample examined, the data from DataStream is consistent with the data from annual reports.

Table 4.2.6c investigates data integrity by comparing firm-earnings data obtained from DataStream to the data in the annual financial statements. I focus on a sample of extreme observations. I find that, for the sample examined, the data from DataStream reflects the data in original reports. Several firms report negative earnings over several periods. These negative earnings deplete firm equity over time. Large negative earnings and low equity values leads to the extreme negative ratios for profitability. Similarly, some firms report negative capital employed (due to low or negative shareholder equity accompanied by high leverage). This often leads to extremely low profitability ratios. This observation persists when other measures of profitability (such as return on assets and return on sales) are employed.

Sales growth is another variable with seemingly extreme observations. For example, the minimum sales growth in panel A is –100% and the maximum sales growth is 3700%. The

–100% sales growth arises as several firms report positive sales followed by close to zero sales in a number of consecutive years. This leads to a sales growth of –100% in the first year. I also find that several energy and mining firms report zero sales in the early years after listing. As deduced from their annual reports, these firms are generally focused on investing in exploratory activities. Small sales followed by very large sales leads to the observation of extreme positive values of sales growth. To evaluate the integrity of this data, I also obtain source documents for a sample of firms with extreme sales growth ratios. Table 4.2.6d presents some of the reasons why some firms in the sample examined report negative or very low sales in a number of years.

Table 4.2.6d: Reasons why firms report zero (or very low) sales in a number of years

Company	Year	Total sales – Perfect Information	Rationale for reporting zero revenues
Medavinci PLC	2006-2010	0 million	Relatively inactive company (no sales) – with several dormant subsidiaries.
Huy PLC	2008	0 million	Disposal of key subsidiaries, hence sales for continuing operations equal £0 million.
Alba Mineral Resources	2005-2009	0 million	Projects still at early stage of development
Alexander Mining PLC	2004-2007	0 million	Newly listed mining company, exploration costs incurred pending any sales. Revenues generated from 2008 onwards.
Copper Resources Corporation	2002-2005	0 million	Newly (2005) listed mining company with a portfolio of investments and no history of sales.
Agcert International PLC	2002-2005	0 million	New listed company, with no history of sales. Sales in 2005 worth only £3,000.

Notes: The table shows some of the reasons why a sample of firms report very low or zero sales in a number of years. Most firms (e.g., Alexander Mining and Copper Resource Corporation) report low or zero sales when they are newly listed. Other firms (e.g., Medavinci PLC) report zero sales due to periods of inactivity and eventual bankruptcy. A majority of the companies with zero sales are newly formed mining and energy companies. Other examples in this category include Peninsular Gold PLC, Sound Oil PLC, Thor Mining PLC, Clontarf Energy PLC, Shanta Gold Ltd, Empyrean Energy PLC, Latitude Resources PLC, Anglo Asian Mining PLC, Sirius Minerals PLC. I also find that these companies are generally delisted after a number of years, perhaps, due to acquisitions or bankruptcies.

Table 4.2.6d shows some of the reasons why firms report very low (or zero) sales in a number of years. Some firms in my sample report very low (or zero) sales in the early years of listing on the stock exchange. This is the case with several energy and mining firms. High sales followed by low sales or the reverse, leads to extreme values of sales growth.

Besides profitability and sales growth, book to market ratios as well as leverage ratios also appear to contain some implausible values. This is due to the presence of negative equity values in DataStream. Following Powell and Yawson (2007), book value of equity is computed as the equity capital and reserves minus total intangibles and leverage is computed as the debt to equity ratio. I find that DataStream reports negative equity values (for several firm-year observations), hence leading to negative book to market and leverage ratios. To assess the integrity of this data, I obtain original annual reports for a sample of firms with negative book values and compare these with the data reported by DataStream.

Table 4.2.6e: Comparing 'total shareholder equity' data from DataStream to data from source documents

Company	Year	Total shareholders' Equity – DataStream (£ million)	Reported equity in consolidated balance sheet (£ million)
Go-Ahead Group PLC	2009	-19.100	-19.100
CVS Group PLC	2008	-1.620	-1.620
Rank Group PLC	2007	-13.300	-13.300
Yell Group PLC	2002	-49.900	-49.900
Britvic PLC	2010	-30.700	-30.700
Premier Foods PLC	2005	-18.000	-18.000
William Hill PLC	2001	-48.739	-40.700
CRP Leisure PLC	1993	-0.013	-0.013
Stanhope Properties	2004	-14.682	-14.682
Premier Health Group	1997	-4.498	-4.498

Notes: The table compares 'total shareholder equity' data from DataStream to data obtained from source documents (annual reports) available from Perfect Information. I find that, for the sample examined, the data from DataStream is consistent with the data from annual reports. Besides the above, other firm years with negative equity (and book) values in their annual reports include: Healthcare Holdings (2001), LP Hill PLC (2009), Vimio PLC (2003), Xploite PLC (2001), Argonaut Games PLC (1999) and Heart of Midlothian (1996), amongst others. I find that many firms report negative equity in the early years of listing, perhaps, due to net losses on operations.

Table 4.2.6e compares the data for 'total shareholder equity' obtained from DataStream to the data from annual reports for a sample of firms with negative equity values.

In general, the review suggests that the data from DataStream is consistent with the data in source documents. The results from tables 4.2.6c, 4.2.6d and 4.2.6e suggest that the data available on DataStream reflects the data in annual reports. It appears that the extreme observations are genuine and are not due to data integrity issues. Nonetheless, these extreme observations cannot be left in the sample as they can potentially distort statistical inferences. Panel B and C of table 4.2.6b explores different techniques for eliminating outliers.

I adopt a winsorising approach (which involves the replacement of extreme values with threshold values) as opposed to an elimination approach (which eliminates extreme values) as it does not result in the loss of data. As seen in panel B, the use of the 1st and 99th percentile winsorising approach still yields a data distribution (for sales growth, financial distress, free cash flow and payroll synergies) with some extreme values. For example, the minimum and maximum profitability ratios are -366.00% and 244.45%, respectively. The minimum and maximum sales growth levels are -87.61% and 793.77%.

As shown in panel C, winsorisation at the 5th and 95th percentile (in line with Christidis and Gregory (2010)) appears to substantially improve the distribution of most of the variables. With the exception of residual volatility, all variables have skewness statistics below the 3 threshold. The distribution of the variables is likely to be more normal leading to more reliable results from empirical analysis. Also, the mean values are more plausible and much closer to the median values. For example the mean (median) profitability is now about 8.52% (11.78%). There is an improvement in the range with the minimum and maximum values appearing to be more plausible. For example, the minimum and maximum profitability ratios are -65.34% and 59.79%, respectively. The minimum and maximum sales growth levels are -38.59% and 137.88%. The descriptive statistics are fully discussed in chapter 5. This winsorising approach (5th and 95th percentile) and the results in panel C are therefore adopted for the rest of the analysis. Some sensitivity analyses are conducted and the results (presented and discussed in section 5.4) suggest that the conclusions do not substantially change even if the winsorisation approach specified in panel B (1st and 99th percentile) is adopted.

4.2.7 Summary

This section discusses the sample and data employed in the empirical analysis in this study. The study uses a sample of public listed UK firms drawn from the period between 1988 and 2009. The data clean-up criteria results in the elimination of several firms which do not meet the criteria for inclusion. This clean-up process generates a final sample 2,970 firms made up of 1,172 active firms, 1,773 dead firms and 25 suspended firms. The required financial data to compute proxies for the old and new hypotheses for each of the 2,970 firms is obtained from DataStream for the full period for which data is available (i.e., between 1988 and 2009). This data collection process generates a panel data set of 32,363 firm-year observations. Data for 2,799 acquisition bids for UK public targets made between 1st July 1989 and 30th June 2011 is collected from Thomson OneBanker. Other required M&A related data required for the analysis is also obtained from Thomson OneBanker. Data from the two databases (Thomson OneBanker and Thomson DataStream) is matched using the June approach (discussed in section 4.2.5) that aligns a firm's financial characteristics in the current period to its takeover probability in the next period. This procedure takes account of the lag between firms' financial year-end and time at which financial statements are publicly available. The final step in the development of the database is the identification and elimination of extreme values by winsorising at 5th and 95th percentile. This process leads to the generation of a clean dataset to be used in the derivation (and evaluation) of the takeover prediction model.

4.3 Methodology for hypotheses validation – Chapter 5

4.3.1 Overview

Chapter 5 is the first of three empirical chapters discussing the results from the analysis. This chapter (5) tests the validity and significance of the hypotheses which were developed in chapter 3. This section discusses the methodology used in chapter 5 for validation of hypotheses. The hypotheses are validated both through univariate and multivariate analysis (section 4.3.2). The hypothesised curvilinear relationships are tested for robustness using alternative methods (section 4.3.3). The old and new variables are combined to generate the new model (section 4.3.4) and the model is tested for intertemporal variation of parameters (section 4.3.5).

4.3.2 Univariate and multivariate analysis

Univariate methods (parametric and non-parametric) are used to conduct preliminary analysis on the validity of the prediction variables and hypotheses employed in this study. These tests evaluate the effect of each individual independent variable on a firm's takeover probability. These tests include: the difference of means test (*t*-test), the independent samples median test (M test) and the Mann Whitney U test (U-test). The *t*-test evaluates the hypothesis that the mean of a variable is the same across targets and non-targets[139]. The 'M-test' tests the hypothesis that the median of a variable is the same across targets and non-targets. The 'U-test' tests the hypothesis that the distribution of a variable is the same

[139] Given the nature of the data, it is unclear whether the variance of the variables for the target and non-target subgroups is equal. The nature of the variances will dictate the appropriate test to use. To investigate this, Levene's Test for equality of variances is conducted at a 5% level. These results obtained from the test determine whether equal variances should or should not be assumed in difference of means tests.

across targets and non-targets. These tests allow for a statistical determination of whether the difference in the mean (*t*-test), median (M-test) or distribution (U-test) of a variable across the targets and the non-targets subgroups is statistically significant within a certain confidence level.

The univariate analyses are augmented with multivariate analyses which allow for the effects of other independent variables to be controlled for while testing the significance of each variable. Several multivariate models have been proposed and used in the literature for discriminating between potential targets and non-targets. Amongst these are linear models such as multiple linear discriminant models, logit models, multinomial logit models, probit models and hazard models (Palepu (1986), Powell (2004), Brar (2009), Ouzounis et al. (2009), Cornett et al. (2011), Bhanot et al. (2010) and Cremers et al. (2009)). Other data mining and nonlinear models such as support vector machines, decision trees, rough set models, neural networks, recursive partitioning and multicriteria discriminant analysis have been applied (see, for example, Espahbodi and Espahbodi (2003) and Pasiouras et al. (2007))[140].

Despite the proliferation of different models, the logit model has remained popular as a base model for takeover prediction modelling. The logit model is based on logistic regression analysis which models a sigmoid-shaped relationship between the probability of a particular outcome for a binomially distributed response variable and a linear combination of explanatory variables (Moutinho and Hutcheson (2011)). The popularity of logit models in takeover prediction can be attributed to two core strengths of the model – (1) Robustness to the statistical properties of accounting variables (see Press and Wilson (1978), Walter (1994) and Barnes, (2000)), and (2) Theoretical relevance and analytical tractability (see Palepu (1986) and Barnes (2000)). The logit model is only restricted by the assumption that the explanatory variables are truly independent i.e., no multicollinearity exists between explanatory variables (Barnes (2000)). The model is robust to the distribution of the independent variables (see Press and Wilson (1978) and Cox (1970)). The assumption of independence can be tested by computing variance inflation factors or examining the correlation matrix (Moutinho and Hutcheson (2011)) – further discussed below.

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[140] Table 2.6.6 (chapter 2) shows the different methods that have been used by different researchers to develop takeover prediction-type models. As discussed in section 2.6.2, the logit model is more suitable for this study when compared to these non-parametric techniques.

Palepu (1986) argues that 'whether or not a firm is acquired in a particular period depends on the number and types of acquisition bids it receives in that period. The number (and types) of bids a firm receives depends on the firm's characteristics as well as the motives of the bidder' (p. 15). In his model, the attributes of the target which cannot be quantitatively measured as well as the characteristics of the target-bidder combination are assumed to be stochastic. This position is slightly extended (in section 3.4) by hypothesising that a firm's probability of being acquired will depend on a broader range of factors including some macroeconomic considerations. These factors are proxied by quantitative variables and enter the model explicitly.

Assuming that there are many acquirers in the market and that acquirers' acquisition motives are stochastic, the probability of a firm being acquired can be modelled as a logit function of its characteristics and its operating environment (Palepu (1982)). The logit function therefore classifies the firm as a target or non-target based on its conditional or posterior takeover probability (Espahbodi and Espahbodi (2003)). This classification is done by computing the odds of the firm being a takeover target in period *t* conditional upon its observed characteristics and attributes prior to period *t*. The logit model is used as the primary method to test the hypothesised linear and curvilinear (U-shape and inverted U-shape) relationships. The methodology for testing the significance of hypothesised linear relationships is standard and involves the analysis of standard errors and p-values. The Regression Analysis of Time Series (RATS) statistical package (version 8) is employed as this allows for the computation of heteroscedasticity-consistent (or White's) standard errors. The sample used in the study consists of repeated observations – i.e., each firm is observed over several years. As a robustness check, the Data Analysis and Statistical Software (STATA – version 12) is also used to estimate clustered standard errors.

The hypotheses development section of the study is focused on developing a comprehensive range of predictive variables to ensure that all relevant variables are considered. This approach leads to the development of a broad range of variables. Some of these variables are likely to be correlated to a certain degree. The inclusion of correlated (or collinear) independent variables in the prediction model is likely to give rise to wide confidence intervals and inflated standard errors (see Brookes (2008), Gujarati (2003)), although the model parameters are still likely to be 'BLUE' – Best Linear Unbiased Estimators (see Brookes (2008), p. 173). The 'wide confidence intervals and inflated standard errors' might result in a false non-rejection of the null hypothesis that coefficients (betas) of affected variables are equal to zero (Brookes (2008)). The level of multicollinearity between the variables employed in this study is inspected by computing bivariate correlations, variance inflation factors (VIF) and tolerance.

Table 4.3.2a shows correlation matrices with Pearson product moment correlation coefficients (parametric) and Spearman's rho (non-parametric) for the main variables in the model.

Table 4.3.2a Panel A: Pearson Correlation Matrix – Bivariate correlation coefficients of independent variables

			V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15
ADAR	**V1**	P. Corr															
Profitability	**V2**	P. Corr	0.052														
		Sig.	0.000														
Book to Market	**V3**	P. Corr	0.017	-0.028													
		Sig.	0.006	0.000													
Sales Growth	**V4**	P. Corr	-0.017	-0.010	-0.157												
		Sig.	0.007	0.087	0.000												
Firm Size	**V5**	P. Corr	0.017	0.256	0.061	-0.090											
		Sig.	0.006	0.000	0.000	0.000											
FCF	**V6**	P. Corr	0.070	0.555	0.103	-0.130	0.453										
		Sig.	0.000	0.000	0.000	0.000	0.000										
Liquidity	**V7**	P. Corr	-0.007	-0.253	-0.095	0.082	-0.274	-0.259									
		Sig.	0.256	0.000	0.000	0.000	0.000	0.000									
Leverage	**V8**	P. Corr	-0.011	0.027	-0.108	-0.010	0.224	0.075	-0.276								
		Sig.	0.073	0.000	0.000	0.093	0.000	0.000	0.000								
Tangible Assets	**V9**	P. Corr	-0.002	0.098	0.352	-0.076	0.275	0.094	-0.389	0.157							
		Sig.	0.733	0.000	0.000	0.000	0.000	0.000	0.000	0.000							
Age	**V10**	P. Corr	0.013	0.129	0.263	-0.198	0.285	0.218	-0.221	0.036	0.204						
		Sig.	0.049	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000						
ZSCORE	**V11**	P. Corr	0.002	0.033	0.034	0.029	-0.096	0.068	0.398	-0.324	-0.207	-0.060					
		Sig.	0.777	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000					
Payroll Expenses	**V12**	P. Corr	-0.037	-0.464	-0.163	0.070	-0.415	-0.559	0.400	-0.136	-0.208	-0.220	0.056				
		Sig.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000				
HHI	**V13**	P. Corr	0.025	-0.079	0.018	0.062	0.023	-0.051	0.023	0.003	0.127	-0.092	-0.026	0.024			
		Sig.	0.000	0.000	0.003	0.000	0.000	0.000	0.000	0.579	0.000	0.000	0.000	0.000			
LIBOR-BOEBR	**V14**	P. Corr	-0.014	-0.031	0.036	-0.069	0.037	0.044	-0.008	0.013	-0.007	0.000	-0.011	-0.005	0.003		
		Sig.	0.027	0.000	0.000	0.000	0.000	0.000	0.172	0.018	0.240	0.968	0.058	0.426	0.646		
FTSE Change	**V15**	P. Corr	-0.123	0.080	-0.008	0.030	0.006	0.035	-0.014	0.002	0.067	0.030	0.014	-0.075	-0.050	-0.280	
		Sig.	0.000	0.000	0.187	0.000	0.280	0.000	0.014	0.701	0.000	0.000	0.020	0.000	0.000	0.000	
Residual Vol.	**V16**	P. Corr	0.047	-0.154	-0.009	-0.015	-0.121	-0.164	0.011	0.084	-0.004	-0.074	-0.042	0.103	-0.031	-0.035	-0.102
		Sig.	0.000	0.000	0.153	0.017	0.000	0.000	0.079	0.000	0.534	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The table shows Pearson product-moment correlation coefficients between the independent variables in the study and the P. value of the correlation statistic for a two tailed test. The variables are shown as V1 to V16 (variable 1 to variable 16) on the horizontal and vertical axis with their associated hypothesis and variable shown in the first column.

Table 4.3.2a Panel B: Spearman Correlation Matrix – Bivariate correlation coefficients of independent variables

			V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15
ADAR	**V1**	P. Corr															
Profitability	**V2**	P. Corr	0.066														
		Sig.	0.000														
Book to Market	**V3**	P. Corr	0.015	-0.116													
		Sig.	0.019	0.000													
Sales Growth	**V4**	P. Corr	0.012	0.159	-0.180												
		Sig.	0.060	0.000	0.000												
Firm size	**V5**	P. Corr	0.034	0.242	0.075	-0.019											
		Sig.	0.000	0.000	0.000	0.002											
FCF	**V6**	P. Corr	0.086	0.529	0.022	-0.003	0.370										
		Sig.	0.000	0.000	0.001	0.608	0.000										
Liquidity	**V7**	P. Corr	0.011	-0.107	-0.147	0.043	-0.147	-0.041									
		Sig.	0.072	0.000	0.000	0.000	0.000	0.000									
Leverage	**V8**	P. Corr	0.000	0.095	0.017	0.014	0.362	0.100	-0.406								
		Sig.	0.943	0.000	0.004	0.019	0.000	0.000	0.000								
Tangible Assets	**V9**	P. Corr	0.003	0.104	0.391	-0.059	0.296	0.095	-0.364	0.298							
		Sig.	0.655	0.000	0.000	0.000	0.000	0.000	0.000	0.000							
Age	**V10**	P. Corr	0.024	0.157	0.292	-0.201	0.320	0.252	-0.216	0.165	0.255						
		Sig.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000						
Z SCORE	**V11**	P. Corr	0.028	0.237	0.167	0.098	0.029	0.276	0.366	-0.491	-0.178	0.032					
		Sig.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000					
Payroll Expenses	**V12**	P. Corr	-0.028	-0.319	-0.194	-0.042	-0.392	-0.289	0.214	-0.192	-0.161	-0.174	-0.106				
		Sig.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000				
HHI	**V13**	P. Corr	0.033	-0.180	-0.128	0.025	-0.010	-0.070	0.076	-0.032	-0.032	-0.181	-0.112	0.027			
		Sig.	0.000	0.000	0.000	0.000	0.082	0.000	0.000	0.000	0.000	0.000	0.000	0.000			
LIBOR-BOEBR	**V14**	P. Corr	-0.033	-0.028	0.036	-0.065	0.042	0.035	-0.006	0.015	0.003	0.020	-0.021	-0.013	0.024		
		Sig.	0.000	0.000	0.000	0.000	0.000	0.000	0.255	0.006	0.619	0.001	0.000	0.052	0.000		
FTSEChange	**V15**	P. Corr	-0.098	0.062	-0.017	0.036	-0.011	0.027	0.009	0.008	0.047	0.006	0.045	-0.058	-0.119	-0.269	
		Sig.	0.000	0.000	0.005	0.000	0.045	0.000	0.106	0.146	0.000	0.334	0.000	0.000	0.000	0.000	
Residual Vol.	**V16**	P. Corr	-0.046	-0.041	0.057	-0.064	-0.029	-0.076	-0.089	0.105	0.089	-0.007	-0.106	-0.021	-0.194	-0.040	-0.203
		Sig.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.276	0.000	0.004	0.000	0.000	0.000

Notes: The table shows Spearman's rho between the independent variables in the study and the p value (two tailed test) of the statistic. The variables are shown as V1 to V16 (variable 1 to variable 16) on the horizontal and vertical axis with their associated hypothesis and variable shown in the first column.

Table 4.3.2a shows a significant correlation (with very low p–values) between most of the key variables used in the study. Nonetheless, the level of correlation appears to be modest (i.e., the Pearson and Spearman bivariate correlation coefficients are close to zero in most cases) and such a level of correlation is unlikely to lead to substantial problems of multicollinearity. The main exception is the free cash flow variable which is moderately correlated to profitability (correlation coefficient: 0.555), payroll expenses (correlation coefficient: -0.559) and firm size (correlation coefficient: 0.453). Payroll expense (as a proportion of total sales) is also moderately correlated to firm size (correlation coefficient: -0.415) and liquidity (correlation coefficient: 0.400). Some overlap between the free cash flow, liquidity and payroll expenses was anticipated (see section 3.4) as firms with high expenses are likely to have low available free cash flow. Some overlap between leverage, payroll expenses and free cash flow was also expected. The correlation between measures of leverage and free cash flow, as well as, leverage and payroll synergies appears to be low.

Tolerance and variance inflation factors (VIF) are, arguably, better measures of the level of multicollinearity as they consider the possibility that one independent variable can be a function of two or more other independent variables (Brookes (2008)). The Tolerance assesses how much multicollinearity can be tolerated in the model[141]. The VIF measures the proportion of the inflation in standard errors resulting from multicollinearity. Tolerance and VIF for all variables in the model are shown in table 4.3.2b. In the absence of the polynomial terms, the VIFs for all variables are low (below 3.00) and tolerances for all variables are high (above 0.30). This level of multicollinearity is, perhaps, not a problem as it is well below the recommended VIF threshold of 10 (see O'Brien (2007) for a literature review on recommended VIFs). This suggests that the level of multicollinearity in the model is modest. As expected, the inclusion of the polynomial terms leads to a substantial increase in the VIFs and tolerances of their related terms. The VIF of firm size increases from 1.46 to 88.98 when firm size squared is added to the model. The results show that the standard errors of the polynomial terms are likely to be substantially inflated leading to a rejection of the underlying hypotheses.

[141] It is computed as $(1-R^2)$, where R^2 is the coefficient of determination obtained by regression the variable on all other independent variables.

T able 4.3.2b: Tolerance and Variance Inflation Factors

Hypothesis/Variable		Without polynomial terms		With polynomial terms	
		Tolerance	VIF	Tolerance	VIF
1	ADAR	0.971	1.030	0.969	1.032
1	Profitability	0.367	2.723	0.366	2.732
1	LMDummy	0.368	2.720	0.365	2.739
2	Book to Market	0.544	1.838	0.537	1.861
2	NBVDummy	0.582	1.717	0.564	1.772
3	Idummy	0.943	1.060	0.941	1.062
4	FCF	0.556	1.798	0.502	1.994
5	Sales Growth	0.907	1.103	0.891	1.123
5	Liquidity	0.622	1.607	0.605	1.654
5	GRDummy	0.920	1.087	0.910	1.099
6	Tangible assets	0.664	1.507	0.653	1.532
7(9)	Firm size	0.664	1.506	0.005	189.375
7(9)	Firm size sq.	–	–	0.005	185.778
10	Leverage	0.775	1.290	0.078	12.742
10	Leverage sq.	–	–	0.086	11.688
11a	Z SCORE	0.707	1.414	0.623	1.606
11b	ZSDummy	0.651	1.537	0.644	1.552
8(12)	AGE (Inc)	0.830	1.205	0.069	14.466
8(12)	AGE (Inc) Sq	–	–	0.073	13.689
13	Rumours	0.988	1.012	0.988	1.012
14	Payroll Expenses	0.587	1.703	0.098	10.221
14	Payroll Expenses Sq.	–	–	0.096	10.465
15	SRDummy	0.989	1.011	0.988	1.012
16	Residual Vol.	0.865	1.156	0.862	1.160
17	HHI	0.934	1.071	0.926	1.080
18	LIBOR-BOEBR	0.889	1.125	0.889	1.125
19	FTSEChange	0.842	1.188	0.840	1.191

Notes: The table shows tolerance and variance inflation factors (VIFs) for all the variables in this study. 'Without polynomial terms' represents the results (Tolerance and VIFs) when the squared (polynomial) terms are excluded from this analysis. The results show that all VIFs are below the 10 threshold proposed by O'Brian (2007) The squared terms are highly correlated with their original variables hence increasing the VIF. The computation of these proxies as well as variable definitions is discussed in chapter 3. ADAR is the average daily abnormal return. Profitability is the ratio of EBITDA to total capital employed. LMDummy takes a value of 1 when a firm makes a loss and a value of 0 otherwise. Book to market (BTM) is the ratio of book value of equity to market value of equity. NBVDummy takes a value of 1 when a firm's BTM is negative and a value of 0 otherwise. Sales growth is the rate of change in total revenues from the previous period. Liquidity is the ratio of cash and short term investments to total assets. Leverage is the firm's debt to equity ratio. GRDummy takes a value of 1 when there is a mismatch between a firm's growth opportunities and its resources and a value of 0 otherwise. IDummy takes a value of 1 if a takeover occurs in a firm's industry and a value of 0 otherwise. FCF/TA is the ratio of free cash flow (operating cash flow less capital investments) to total assets. PPE/TA is the ratio of tangible assets (property, plant and equipment) to total assets. Age is the number of years since incorporation. Ln Assets is the natural log of a firm's total assets. SRDummy takes a value of 1 if a firm announced any share repurchases in the period and a value of 0 otherwise. MRDummy takes a value of 1 if a firm is the target in a merger rumour and a value of 0 otherwise. ZScore is a firm's Taffler Z Score. ZSDummy takes a value of 1 if a firm has a negative Z Score and a value of 0 otherwise. HR Cost to sales is the ratio of payroll expenses to revenues. Herfindahl index is the concentration of the firm's industry in a particular year. Residual volatility is the standard deviation of a firm's abnormal return in the year to June 30th. FTSEChange is the performance of the FTSE All Share index in the year to June 30th. LIBOR-BOEBR is the spread between the LIBOR and the Bank of England's base rate.

Given the likelihood of bias in the p-values (t-statistics and standard errors) for polynomial terms, a further robustness test of curvilinear relationships is conducted. This is discussed in section 4.3.3. It is worth reiterating that the use of models with polynomial terms is standard practice in contemporary accounting and finance literature (see, for example, Cornett et al. (2011)).

In the modelling, I also consider the impact of selected variables by testing alternative models. In all regression analyses, I start with a univariate model with only one independent variable. As will be discussed in chapter 5, the addition of other control variables does not change the initial results in most cases. In chapter 6, I also examine the performance of models with and without some of the proposed independent variables. The results in chapter 6 (section 6.2) show that models with all the proposed independent variables outperform models without the variables.

4.3.3 Robustness test of curvilinear relationships

As discussed in section 3.4, the curvilinear relationships (e.g., for firm size) are tested by adding a squared term of the key variable (i.e., firm size squared) to the model and testing for its statistical significance in the model. This technique for testing for the existence of quadratic or curvilinear trends (U-shape and inverted U-shape relationship) is popular in the finance literature (see, for example, Loderer and Waelchli (2010)). It is, however, noted that this technique generates multicollinearity problems (as discussed in 4.3.2) which might impact on the interpretation of the results obtained. I attempt to alleviate this problem by conducting two further robustness tests for the four hypothesised curvilinear relationships (i.e., firm size, leverage, payroll and firm age).

The first robustness check involves centering the proxies of the four hypotheses. The test variable (i.e., firm size) is centered about its mean and the square of the centered variable is computed. Centering around the mean potentially reduces the collinearity problem while also allowing for the squared term to be interpreted without reference to the key variable (Aiken and West (1991)). That is, the statistical significance of the squared term (irrespective of the level of significance of the key variable) suggests a significant curvilinear relationship. The second robustness check involves the use of piecewise regression analysis. Piecewise regression analysis models the curvilinear relationship in a different way by assuming the existence of breakpoints in the relationship between takeover probability and the key variable (i.e., firm size) and testing for changes in beta (see Gujarati (2007)). For simplicity, I consider four firm size breakpoints (equivalent to 20th, 40th, 60th, and 80th percentiles in the firm size distribution). I run the model at different breakpoints (e.g., for firm size between 0 and 20th percentile, 20th and 40th percentile, 40th and 60th percentile, 60th and 80th percentile, and 80th and 100th percentile) and analyse the sign and significance of the coefficients (beta) of the key variable. The model is shown below.

$$Logit(P_i) = \begin{cases} \gamma_0 + \gamma X_{1,i} + \sum \gamma_m X_{m,i} + \varepsilon, & X_{1,i} \leq p20 \\ \delta_0 + \delta X_{1,i} + \sum \delta_m X_{m,i} + \varepsilon, & p20 < X_{1,i} \leq p40 \\ \pi_0 + \pi X_{1,i} + \sum \pi_m X_{m,i} + \varepsilon, & p40 < X_{1,i} \leq p60 \\ \theta_0 + \theta X_{1,i} + \sum \theta_m X_{m,i} + \varepsilon, & p60 < X_{1,i} \leq p80 \\ \omega_0 + \omega X_{1,i} + \sum \omega_m X_{m,i} + \varepsilon, & X_{1,i} > p80 \end{cases} \quad \ldots\ldots\ldots Eqn\ 4.3.3(1)$$

Where, $\sum N_m X_{m,i}$ is a set of control variables, $NX_{1,i}$ is the key variable with slope N, N_0 is the constant term, ε is the error term and pN refers to the Nth percentile for variable $X_{1,i}$.

As shown in equation 4.3.3 (1), the key variable under test is X_1. The piecewise regression model allows the slope of X_1 to change at different points of the distribution. If the hypothesis predicts an inverted U-shape relationship between X_1 and takeover probability (P_i), then it is expected that the coefficient of γ should be positive and the coefficient of ω should be negative (and statistically significant). The coefficients of δ and θ could also, perhaps, be positive and negative (respectively) depending on the degree of curvature in the relationship.

4.3.4 The (new) takeover prediction model

The new model is a model which combines the new hypotheses (variables) and the old hypotheses (variables), discussed in section 3.3 and 3.4, under a predictive modelling framework. The model postulates that the probability of a firm receiving a bid in the next period is a (logit) function of a vector of 27 firm-related, industry-related and market-related variables observed in the current period. The hypotheses and independent variables employed in the takeover prediction model are developed in chapter 3. The basic model is shown below.

$$Logit(P_{it}) = Ln\left(\frac{P_{it}}{1 - P_{it}}\right) = \beta . X_{it-1} \ldots\ldots\ldots Eqn\ 4.3.4(1)$$

P_{it} is the takeover likelihood of firm *i* at time *t* and X_{it-1} is a vector of 27 variables for firm *i* at time *t*-1. P_{it} can be computed as the inverse of the logit function – i.e., the logistic function – as shown below.

$$P_{it} = Logit^{-1}(\beta . X_{it-1}) = \frac{1}{1 + e^{-\beta . X_{it-1}}} \dots \dots \dots Eqn\ 4.3.4(2)$$

The model coefficients (β) are estimated using the maximum likelihood estimation technique with RATS computer software. This method generates the set of coefficients which optimises the likelihood of observing the underlying data (further discussed in Long and Freese (2006)). As noted in section 4.3.2, a main concern in pool regression analysis is the potential correlation of residuals across firms, industry and time when a panel data set is used (Powell and Yawson (2007)). In the first instance standard errors are corrected for heteroscedasticity obtaining Huber-White (robust) standard errors. The pooled estimation model computes robust standard errors under the assumption that these standard errors are uncorrelated across firms, industry and time. Evidence from Mitchel and Mulherin (1996) suggests that takeovers potentially cluster across industries and over time. To resolve this issue, robust standard errors are corrected for clustering by using the Rogers (1993) method for correcting standard errors for correlation with a cluster (e.g., firm, year, industry) – Rogers (clustered) standard errors. This methodology for correcting for clustering (Rogers standard errors) has been applied in other studies such as Powell and Yawson (2007).

4.3.5 Model stability: Test of intertemporal variation in target characteristics

Sections 4.3.2 and 4.3.3 discuss the methodology for hypotheses testing. These tests are conducted over the entire study period. Powell (1997) suggests that the characteristics of targets can exhibit intertemporal variation. That is, the characteristics of targets can be unstable through time. If this is the case, the new model (discussed in section 4.3.4) is likely to lack consistency and robustness in its performance across time. Shorter estimation periods have been used in an attempt to mitigate the effect of intertemporal variation (see, for example, Espahbodi and Espahbodi (2003))[142]. The downside to this approach is the significant loss of information and, perhaps, the inability to generalise the findings of the study. Powell (1997) neither provides a statistical test to support his argument of

[142] Espahbodi and Espahbodi (2003) employ data from July 1997 to December 1997 (6 months) to estimate their models.

intertemporal variation nor discuss the reasons for such variations (also see Thomas (1997) for a critique of Powell (1997)).

Powell (1997) finds that some variables which were significant predictors of takeover likelihood in the 1984–1987 period were insignificant in the 1988-1991 period. Statistics provided by Harford (2005) and Martynova and Renneboog (2008) show that these two periods represent two different phases of the fourth merger wave – a growth in merger activity (1984–1987) and a decline in merger activity (1988–1991). Harford (2005) contends that the 1990–1991 period of economic recession, perhaps, led to a substantial decline in merger activity in this period. This evidence broadly suggests that Powell's finding can partly be attributed to changing macroeconomic conditions across the two estimation samples. Powell (1997) does not control for changes in macroeconomic conditions in his model. The new model is likely to be relatively more stable across time as hypothesis 18 and hypothesis 19 (discussed in sections 3.4.11 and 3.4.12 respectively), perhaps, control for changing macroeconomic conditions. I evaluate this contention by testing the new model for intertemporal variation in target characteristics.

Thomas (1997) discusses a suitable methodology for testing for intertemporal variation in independent variables. The methodology involves comparing the characteristics of targets in one period (period 1) to the characteristics of targets in the next period (period 2) using a logit model. The model used for this test is similar to equation 4.3.4(1). The dependent (binary) variable in the model takes a value of 1 for targets in the second period (period 2) and a value of 0 for targets in the first period (period 1). Given the study period (1988 and 2009), 20 yearly breakpoints (used for the identification of period 1 and period 2) are set from 1989 to 2008. At each breakpoint (e.g., 1990), I investigate whether the characteristics of targets prior to this breakpoint (e.g., 1988–1989) are different from the characteristics of targets after the breakpoint (e.g., 1990–2009). I use the Chi Squared (χ^2) test and *t* test to test the null hypothesis that all model coefficients (betas) are jointly equal to zero and that individual model coefficients are equal to zero, respectively. I conclude that target characteristics do not exhibit intertemporal variation if the null hypothesis cannot be rejected. The results of these analyses are presented and discussed in section 5.5.

4.3.6 Summary

This section discusses the methodology used in validating the hypotheses as well as the development of the prediction model. The problem of potential multicollinearity (mainly due to the polynomial term) is raised. Some of the independent variables, particularly, the profit margin and return on assets, are moderated and highly correlated with other independent variables. As discussed in section 4.3.2, this problem can be resolved by using the variables as substitutes in the model. Further, results from the analysis of variance inflation factors, suggest that the level of multicollinearity within the system of independent variables is insignificant. Section 4.3.3 also discusses key robustness checks for the existence of curvilinear relationships (in line with the hypotheses). These checks include mean centering of squared terms and the use of a piecewise regression analysis model. The development of the new model by combining the old and new variables is also discussed. Finally, a test of model stability (through evaluating the level of intertemporal variation in target characteristics) is discussed. The objective of this final test is to assess whether model parameters are relatively stable and, hence, useful in prediction from one year to another.

4.4 Evaluating model predictive ability – Chapter 6

4.4.1 Overview

This section discusses the methodology employed in chapter 6 to evaluate the new model's performance (i.e., its ability to distinguish between targets and non-target within-sample and its ability to predict future takeover targets). Its performance is ascertained by comparing it with a benchmark model using Receiver Operating Characteristics (ROC) curve and out-of-sample analyses. Section 4.4.2 discusses the development and use of benchmark models for comparison, section 4.4.3 discusses the use of ROC curve analysis and section 4.4.4 discusses the use of out-of-sample performance analysis.

4.4.2 Benchmark models: old and old (balanced) models

The new model is evaluated by comparing its performance with that of a control or benchmark (described as 'old') model. The old model employs the same dataset and methods as the new model but is restricted to the old variables only. The only difference between the old and new model is the fact that the new model has 15 additional prediction variables (the new variables) as shown in table 4.4.2. This makes the old model a suitable benchmark to isolate the effects of the new variables.

Table 4.4.2: Old model versus new model – Variables

Hypotheses	OLD MODEL (Exp. sign)	NEW MODEL (Exp. sign)
Inefficient Management	ROCE(–) ADAR (–)	ROCE (–) ADAR (–) LMDUMMY (+/–)
Undervaluation	BTM (+)	BTM(+) NBVDUMMY (+/–)
GR Mismatch	Sales Growth (+/–) Liquidity (+/–) GRDummy (+)	Sales Growth (+/–) Liquidity (+/–) GRDummy (+)
Industry Disturbance	IDUMMY (+)	IDUMMY (+)
Free Cash Flow	FCF (+)	FCF (+)
Tangible assets	PPP/TA (+)	PPP/TA (+)
Firm Size	Ln Assets (–)	Ln Assets (+) Ln Assets sq. (–)
Capital Structure	Leverage (+/–)	Leverage (+) leverage Sq. (–)
Firm Age	Age (–)	Age (–) Age squared (+)
Share Repurchases		SRDUMMY (+/–)
M&A Rumours		RDUMMY (+)
Payroll Synergies		HR. Cost to sales (+) HR. Cost to Sales Sq. (–)
Financial Distress		Z Score (–) ZSDUMMY (–)
Industry Concentration		Herfindahl Index (–)
Asymmetric Valuation		R&D Intensity (–)
Market Sentiment		FTSEChange (+)
Market Liquidity		LIBOR-BOE (–)
Constant Term	Yes	Yes

Notes: The table shows the independent variables in the old (and old balanced) and new models. These variables are derived from the old and new hypotheses (respectively) as discussed in section 3.2 and 3.3. The new model uses 15 more variables than the old model. The expected sign (i.e., the hypothesised relationship between takeover probability and each variable) is shown in brackets.

In the first instance, an unbalanced panel dataset is employed in the analysis. The new model has 27 variables of which 12 are old variables and 15 are new variables. The use of 27 variables in the new model (as compared to 15 variables in the old model) imposes greater data restrictions on the dataset as complete data is required to run the analysis. Some observations that will be dropped from the new model (due to incomplete data) are maintained in the old model since the data is not required. The effect is that the old model will be tested on a larger dataset than the new model. It is uncertain whether this difference in sample applied for testing can constitute a source of bias in the analysis. To ensure that the difference in the size of the test sample does not introduce bias into the analysis, the coefficients of the old model are redeveloped using a balanced panel dataset. The derived model is referred to as the old (balanced) model. It is worth noting that such a model cannot be replicated in practice without full knowledge of the new variables. It is, hence, only used for testing purposes in this study.

4.4.3 Model comparison using area under Receiver Operating Characteristics (ROC) curves

ROC curve analysis is typically used to evaluate the explanatory power of logit models (Hanley and McNeil (1982) and DeLong et al. (1988)). Simply put, a ROC curve is a graphical plot that depicts the performance of a binary classification system or model (such as logit model) as the discrimination threshold (i.e., cut-of probability) is varied (Krzanowski and Hand (2009)). As suggested by Krzanowski and Hand (2009), the performance of the model is ascertained by computing the ratio of true positives to total positives (sensitivity) and the ratio of false positives to total negatives (specificity) at different cut-off probability thresholds. True positives are the number of firms predicted as targets that are actual targets. Total positives are the number of targets in the prediction sample. False positives are the type II errors i.e., predicted targets which are actual non-targets. Total negatives are the number of non-targets in the prediction sample. The typical ROC curve is obtained by plotting sensitivity against (1 – specificity).

Once the ROC curve is obtained, a key statistic of interest to the investigator is the area under the ROC curve. As suggested by Hanley and McNeil (1982) and DeLong et al. (1988) the area under the ROC curve is a suitable measure of the predictive power of a logit model. More interestingly, ROC curves have been used to directly compare the performance of two or more logit model. Studies such as DeLong et al. (1988) and Hanley and McNeil (1982, 1983) have developed tests which can be used to directly compare the area under the ROC curve of two or more logit models.

The use of ROC curve analysis is popular in the area of bankruptcy prediction. Studies such as Altman et al. (2010), Christidis and Gregory (2010) and Tinoco and Wilson (2013), amongst others, have employed this technique. To my knowledge, no prior studies in takeover prediction have employed such tests. In this study, besides the use of classic performance measures such as pseudo R squares (Cox and Snell and Nagelkerke R squares) and Hosmer-Lemeshow Goodness of Fit statistic, I use ROC curve analysis to directly compare the new model's performance to the performance of the old (or benchmark) model.

4.4.4 Model comparison using portfolio target concentration

4.4.4.1 Overview

A common and intuitive technique for comparing prediction models is to directly compare their ability to predict an event out-of-sample (see, for example, Palepu (1986), Bartley and Boardman (1986, 1990), Barnes (1998, 1999, 2000), Powell (2001, 2004) and Pasiouras et al. (2007)). The first step in the process is to identify a suitable portfolio selection method. Next, the model coefficients (generated using data in period *t*) are used to compute takeover probabilities out-of-sample (period $t+1$). Firms are then ranked in order of increasing takeover probability and the portfolio selection method is used to identify the target portfolio. The portfolio's target concentration – a measure of predictive ability – is computed as follows.

$$Target\ Concentration = \frac{Number\ of\ predicted\ targets\ that\ receive\ a\ bid}{Total\ number\ of\ predicted\ targets}$$

There are several methods for identifying the target portfolio including the use of cut-off probabilities, fixed-size portfolios (e.g., portfolio of 100 stocks), percentiles, deciles and quintiles. Different methods have been used in prior research with no consensus on what method is optimal. The portfolio selection method is important in this study as the returns to predicted targets (analysed in chapter 7) are based on these portfolios. To avoid any bias due to choice of portfolio selection method, I explore the use of a wide range of portfolio selection techniques. The techniques explored are discussed in sections 4.4.4.2 and 4.4.4.3.

4.4.4.2 Cut-off probabilities for identifying the target portfolio

The logit model (for takeover prediction) reports its output in terms of probability. That is, the model uses its coefficients to transform the independent variables for any observation (firm-year) into a probability value. This probability value represents the likelihood that the firm will receive a bid in the next period based on the publicly available information available about the firm, its industry and the market. The expectation is that the computed probabilities will range from 0 to 1. A key task is to determine a cut-off point over which the computed probability is 'high enough' for the firm to be considered a potential target. While a median break point of 0.5 may sound intuitive (see Palepu (1986) for a discussion), with firms above this breakpoint classified as targets and vice versa, it is empirically unjustified as the number of non-targets far outweigh the number of targets in the sample (Palepu (1986), Powell (2001)).

As noted by Powell (2001), determining an optimum cut-off probability involves a trade-off between the cost of committing a type I error and the cost of committing a type II error[143]. Two major procedures for determining cut-off probabilities have been proposed in the literature by Palepu (1986) and Powell (2001). The two procedures are only slightly different. The difference is based on whether the researcher assumes that the cost of committing a type I error and the cost of committing a type II error are (or are not) equal and constant (Powell (2001)).

The first procedure, proposed by Palepu (1986) and extended in Barnes (1998), is based on an objective to minimise the total number of misclassifications. The underlying objective is to minimise both type I and type II errors since it is assumed that the costs of committing both types of errors are equal (Palepu 1986). The second procedure proposed by Powell (2001) is based on an objective to maximise the proportion (concentration) of targets in the selected target portfolio. This cut-off allows non-targets to be classified as targets only if this markedly increases the number of actual targets (i.e., target concentration) within the takeover portfolio. This is based on the assumption that the cost of a type II error is higher than the cost of a type 1 error. By design, Powell's (2001) method imposes a stricter rule for including each prospective target into the target portfolio.

Arguably, both procedures have merits and demerits and their underlying objectives are both valid. In both cases, cut-off probabilities are computed using ex-ante data. It is assumed that the cost of committing a type I and type II error are constant over time hence cut-off probabilities developed ex-ante are applicable ex-post. Further, the use of ex-ante data to develop cut-off points for predictive tests prevents look-ahead bias in the analysis. As noted by Powell (2001), Palepu's procedure leads to the selection of a lower cut-off probability when compared with Powell's procedure. The implication (as discussed in Barnes (1998) and Powell (2001)) is that target portfolios developed using the Palepu (1986) approach are likely to have a higher number of targets but also a higher number of non-targets misclassified as targets. Powell's procedure aligns with the overall objective of identifying an optimal portfolio within which the proportion of targets is highest and the number of misclassifications of non-targets is lowest. This procedure is very similar to that

143 A type I error is a case where the selected cut-off probability allows a target to be incorrectly classified as a non-target ex-post. Similarly, a type II error is a case where the selected cut-off probability (ex-ante) allows a non-target to be incorrectly classified as a target (ex-post). Type I and type II errors are discussed further in section 4.4.6.

proposed by Barnes (1998, 1999 and 2000). The Powell (2001) procedure for computing optimal cut-off probabilities is adopted in this study[144]. To ensure that the results are not biased by this choice, I also consider other methods of identifying targets, suggested and employed by more recent studies (discussed in section 4.4.4.3).

4.4.4.3 Portfolio sorts for identifying the target portfolio

The use of probability deciles and quintiles to classify targets is common in the literature (see, for example, Brar et al. (2009) and Cremers et al. (2009)). Here, firms in the holdout sample within the top probability decile or quintile (i.e., decile or quintile of firms with the highest takeover likelihood) are simply considered as potential targets. While this is a useful technique from an investment perspective, it can, perhaps, not be theoretically justified. Under this methodology, a firm's likelihood of receiving a bid is a function of the likelihood of other firms receiving a bid. For example, if 20% of firms in a sample have a high takeover probability (say above 0.6), then a firm, *i*, with a takeover probability of 0.5 will fall in a lower decile (or quintile) and will be considered as a non-target. The firm's classification as a target or non-target is therefore contingent on the takeover probabilities of other firms in the holdout sample. Further, the use of deciles (quintiles) implicitly assumes that 10.00% (20.00%) of firms in the holdout sample will receive a bid every year. The UK average, as shown in section 4.2.6, is about 5.05%. The use of cut-off probabilities, potentially, circumvents some of the problems with portfolio sorts. Cut-offs probabilities are developed ex-ante (test sample) and applied ex-poste (holdout sample). The technique is popular in the literature and is used here to ensure comparison and consistency with prior studies.

The empirical evidence on investor diversification tendencies asserts that small investors choose to hold only a small number of stocks in their portfolios mainly due to the transaction costs and management fees involved (Statman (1987) and Goetzmann and Kumah (2008)). For example, after examining the portfolios of over 62,000 US small/individual investors between 1991 and 1996, Goetzmann and Kumah (2008) conclude that the average US individual investor holds between four and six stocks in their

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[144] As discussed in Powell (2001, p. 1000), once takeover probabilities for all firms in the holdout sample are computed, the optimal cut-off probability can be obtained through the following four steps.
(1) Rank the firms in each year by their takeover probabilities.
(2) Construct 10 portfolios of equal sizes – using deciles.
(3) Compute the ratio of actual targets to total firms for each portfolio – target concentration.
(4) Select the lowest takeover probability in the portfolio with the highest target concentration ratio.

portfolio. Similar results for small investors have been reported by Barber and Odean (2000). Using a sample of 123,640 European firms, Faccio et al. (2011) show that the situation is surprisingly not very much different for large investors despite the extensively documented benefits of diversification. Their results show that only 43.5% of large investors are diversified (i.e., hold equity in two or more firms) of which 6.3% (0.87%) hold equity in more than 10 (50) firms and only 0.34% of large investors in Europe (UK inclusive) hold equity in more than 100 firms.

The evidence above suggests that investors might be keen on maintaining a small number of stocks in their portfolio rather than investing in all stocks that meet their investment criteria. The use of cut-off probabilities in prediction models does not allow for the control of the number of predicted targets and therefore might not be a suitable selection criterion for all investors. Consistent with prior studies (Brar et al. (2009), Cremers et al. (2009)), deciles and quintiles of target portfolios are obtained by applying the 'portfolio sorts' methodology. For the purpose of this study and to allow for robustness, several other portfolios sizes, types and strategies are employed. These are summarised in the table (4.4.4) below.

Table 4.4.4: Portfolios employed – Description and rationale

Portfolio	Description or definition	Rationale
Cut off	Portfolio of firms with probability of receiving a bid greater than the cut-off probability attained using the Powel (2001) procedure	The importance of cut-off probabilities is so that an investor using only limited data e.g. data for 20 non-randomly selected firms can analyse them independently to see if they are likely to be targets. Deciles, quintiles require that the whole data set be analysed.
Decile 10 (D10)	Decile (10%) of firms with highest probability of receiving a bid	Convention; employed in studies such as Cremers et al. (2009) and Brar et al. (2009).
Quintile 5 (Q5)	Quintile (20%) of firms with highest probability of receiving a bid	Convention; employed in studies such as Cremers et al. (2009)
Port5%	Portfolio of 5% of firms with highest probability of receiving a bid	Descriptive statistics show that on average 5.05% of UK listed firms between 1989 and 2009 received a bid each year
Port100	Portfolio of 100 firms with highest probability of receiving a bid	None but might be a viable option for large fund managers and institutional investors
Port50	Portfolio of 50 firms with highest probability of receiving a bid	Used by Morgan Stanley Target Equity Index (2003–2011) and Wansley et al. (1983)
Port30	Portfolio of 30 firms with highest probability of receiving a bid	Theoretically approximated as the size of a well-diversified portfolio. Fisher and Lowrie (1970) argue that over 95% of diversification benefits can be captured with a 'diversified' portfolio of 30–32 stocks
Port10	Portfolio of 10 firms with highest probability of receiving a bid	Provides a viable option for small and individual investors

Notes: This table shows the different techniques used to identify the optimal portfolio of predicted targets. It is assumed that all portfolios are constructed and held on the 1st of July in the respective year until the 30 June in the next year (one year holding period). Both equal-weighted and value-weighted portfolios are assessed and the portfolios are rebalanced annually. This is further discussed in section 4.5.

One advantage of cut-off probabilities (section 4.4.4.2) over portfolio sorts is that cut-off probabilities offer more flexibility and real-time prediction. This is particularly important given that firm financial data becomes public at different points in time (discussed in section 4.2.5). A modeller employing cut-off probabilities can determine whether a firm is a potential target at any point when its financial information becomes public. A modeller using portfolio sorts will need to wait until all financial results for all firms in the sample are made public before constructing his/her portfolio. As discussed in section 4.2.5, it is assumed that happens at the end of June each year – the June approach. Further, the use of cut-offs allows a firm's takeover likelihood to be independently determined, i.e., not determined by the likelihood of other firms in the population becoming targets. The ‘portfolio sorts’ methodology implicitly assumes a firm’s takeover likelihood is determined relative to the takeover likelihood of other firms[145].

4.4.5 Summary

Section 4.4 discusses the methodology applied to evaluate the model’s predictive ability. The performance of the new model is directly compared with the performance of two control models (the old and old (balanced) models) using both ROC curve analysis and out-of-sample target portfolio analysis. The old model is a model which is developed using only the old takeover prediction hypothesis. The use of this model as a control model allows for the contribution of the new variables to be empirically determined. The old (balanced) model is an additional robustness check for the effect of sample size differences which involves testing the old model on a balanced sample – exact sample use by the new model. The empirical analysis and tests are conducted over different test samples and different holdout periods. Several methods (including cut-offs and portfolio sorts) are used to identify the target portfolio. The target portfolio is evaluated using a comprehensive performance metric which considers the level of type I and type II errors, the target concentration and the overall model predictive ability. Overall, this method of testing, is perhaps, more extensive and robust, when compared to the methods used in prior studies.

4.5 Evaluating model investment potential - Chapter 7

A key research question this study seeks to explore is whether takeover prediction can form the basis of a successful investment strategy. This builds on prior research findings that takeover targets gain substantial abnormal returns during the period surrounding the takeover announcement. Chapter 6 focuses on developing portfolios of firms which are predicted to receive takeover bids in the next period. This sub-section discusses the methods used in the computation of the abnormal returns earned by these portfolios.

Portfolio abnormal returns are computed following the calendar-time portfolio approach discussed in Ang and Zhang (2004). The first step in this process is computing the portfolio returns from stock returns. This is done as follows. Monthly discrete (or simple) returns are computed from the return index [RI] DataStream data-type which represents

[145] For example, a firm with takeover probability of 0.7 will only be included in a target portfolio (obtained from deciles) if its takeover probability is higher than the takeover probability of 90% of the population. An established cut-off probability of 0.67, will mean that such a firm will be included in the target portfolio even if 80% of the firms in the population have a takeover probability greater than 0.67.

share prices adjusted for dividend payments. The monthly discrete returns for each stock are computed for the period July year t (X1) to June year $t+1$ (X2) to coincide with the portfolio holding period as discussed in section 4.2.5 – the June approach. Simple firm returns are computed as follows.

$$Returns_t = \frac{RI_{t+1} - RI_t}{RI_t} \dots \dots \dots Eqn\ 4.5.1(1)$$

RI_{t+1} and RI_t are the adjusted (for dividends, splits and repurchases) share prices for each stock in month $t+1$ and month t respectively. Unlike prior studies (such as Palepu (1986) and Brar et al. (2009)), which employ a state-based sampling methodology where targets are matched with a sample of (non-randomly selected) surviving non-targets, survival bias is avoided in this study by using a panel data set of both live and dead (delisted) firms. Inadvertently, several of these firms are delisted for different reasons including bankruptcy, liquidation, and administration, amongst others. To ensure that the potential loss associated with these events are accounted for in the analysis, firms that go bankrupt, are suspended or are delisted, are ascribed a return of –100% in the month of bankruptcy (or delisting) and are taken out of the portfolio from the next month.

The methodology for identifying bankrupt firms is consistent with Christidis and Gregory (2010). The data regarding firm status is obtained from the LSPD[146] Database and the LSPD Master Index File which provides a reason of death in each case using different codes: liquidation (7), delisted and all dealings terminated (14), receiver appointed (16), administrative receivership (20), and cancelled or suspended (21)[147]. Individual firms are identified in the LSPD Master Index File using SEDOL codes. These codes are matched with the respective DataStream codes and the '–100%' returns are manually entered for each case in the month in which the delisting takes place.

In line with Cremers et al. (2009), returns are computed for both equal-weighted portfolios and value-weighted portfolios and portfolios are rebalanced annually. Equal-weighted portfolios assume that an equal amount is invested in each firm in the portfolio at the beginning of the portfolio holding period and the portfolio is held until the end of the holding period. The value-weighted portfolios assume that an investor allocates his investment to the stocks in the portfolio in proportion to their market value at the

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146 Source file G Records: G 10 type of Death

147 It is worth noting that firms which are delisted due to a takeover are not treated in the same way as bankrupt or delisted firms.

beginning of the portfolio holding period – June 30th. The average return on the portfolio in month t (denoted average monthly unadjusted return, AMUR) is computed by averaging the returns for each firm in the portfolio in a particular month. (The computation of risk-adjusted returns is discussed in the next section). For equal-weighted portfolios, this is given by

$$AMUR_t = \frac{1}{N}\sum_{i=1}^{N} Returns_{it} \; \dots\dots\dots\dots Eqn\ 4.5.2(2)$$

And for value-weighted portfolios this is given by

$$AMUR_t = \sum_{i=1}^{N} W_i Returns_{it,} \dots\dots\dots Eqn\ 4.5.2(3)$$

Where t is the month for which returns are being computed, N is the number of firms in the portfolio, $Returns_{it}$ is the discrete return on firm i in month t, and W_i is the weight[148] of firm i within the portfolio. The AMUR computed above, therefore, represents the monthly returns on an investor's portfolio (value or equal-weighted) from one month to another.

Annual rebalancing is, potentially, problematic as the weights are subject to the value of the firm on a single day. An alternative to annual rebalancing is monthly rebalancing where the weighting in each stock is adjusted for growth or decline in market value in each month. This method, however, involves active stock trading which increases the portfolio management costs (such as transaction costs and monitoring costs) and, therefore, reduces the potential returns from the strategy.

The second step in the process of computing portfolio abnormal returns is to adjust portfolio returns for risk. This section discusses the models used in the computation of abnormal returns (or risk-adjusted returns) which are obtained by adjusting portfolio returns for risk factors such portfolio risk, market risk and return volatility amongst others. Several approaches (with different strengths and weaknesses) have been employed in the literature in a bid to adjust returns for the risks involved. To allow for robustness and comparison of the results with previous literature, portfolio monthly returns (AMUR) are adjusted for risk by using popular risk adjustment models including the CAPM, Three-

148 Defined (or computed) as the ratio of the market value of the firm to the total market value of the firms in the portfolio at the start of the holding period.

factor model (Fama and French (1992)) and the Four-factor model (Carhart (1997)). The table below shows the specifications of the different models employed.

Table 4.5.3: Risk adjustment models

Panel A: Capital asset pricing model (CAPM)

$$R_{it} - RF_t = \alpha_i + \beta_{mkt}\,(RM_t - RF_t) + \varepsilon_{i,t} \quad \dots\dots\dots Eqn\ 4.5.3(1)$$

Panel B: Fama and French three-factor model

$$R_{it} - RF_t = \alpha_i + \beta_{mkt}\,(RM_t - RF_t) + \gamma_{smb}SMB_t + \tau_{hml}HML_t + \varepsilon_{i,t} \dots\dots Eqn\ 4.5.3(2)$$

Panel C: Four-factor model

$$R_{it} - RF_t = \alpha_i + \beta_{mkt}(RM_t - RF_t) + \gamma_{smb}SMB_t + \tau_{hml}HML_t + \rho_{umd}UMD_t + \varepsilon_{i,t} \dots\dots Eqn\ 4.5.3(3)$$

Note: The table shows different risk adjustment models that are used to compute abnormal returns (alpha) earned by target portfolios. Equations 4.5.3 (1) to 4.5.3 (3) specify the different measures employed in adjusting for portfolio risks. The alpha (α_i) is equivalent to the constant term obtained through regression analysis. This represents the risk-adjusted abnormal return for portfolio *i.*

In these equations (equations 4.5.3 (1) to 4.5.3 (3)), R_{it} is the discrete return (AMUR) on portfolio *i* in month *t*, RF_t is the risk free rate in month *t*, α_t is the abnormal (excess) monthly return or portfolio alpha in the period, RM_t is the market return in month *t*, SMB (Small Minus Big) and HML (High Minus Low) are the Fama & French factors, UMD (Winners Minus Losers) is the momentum factor. SMB (the difference in the returns of value-weighted portfolios of small stocks and big stocks), HML (the difference in the returns of value-weighted portfolios of high book-to-market stocks and low book-to-market stocks) and UMD (the difference in the returns of winners and losers) depict the monthly return on the zero investment portfolio for the common size factor, book to market equity factor and momentum factor in stock returns. $\beta, \gamma, \tau, \rho$ are regression coefficients for the different risk factors. The data for the monthly risk free rate (RF), the monthly market return (RM), and the risk factors (SMB, HML and UMD) for the UK market are obtained from Gregory et al. (2013)[149].

As per these equations, I fit monthly excess portfolio returns ($R_{it} - RF_t$) to excess market return ($RM_t - RF_t$), the size factor (SMB_t), the book to market factor (HML_t) and the momentum factor (UMD_t). The intercept or constant term from this regression provides an estimate of returns that cannot be explained by common risk factors.

149 The data is available freely through this link: http://xfi.exeter.ac.uk/researchandpublications/portfoliosandfactors/
[Last accessed 15 June 2014]

Standard errors obtained are corrected for heteroscedasticity to obtain robust (white) standard errors. Given that the process involves time series regressions of firm returns, for robustness, t-statistics are also estimated using Newey-West standard errors (with up to 5 lags) which correct for heteroscedasticity and autocorrelation in residuals. This analysis is done in STATA. The results are generally similar and the conclusions do not change.

4.6 Chapter summary and conclusion

This chapter discusses the sample selection, data and methodology for the empirical analysis in the study. The study employs a sample of UK firms between 1988 and 2009 for developing and testing the takeover prediction model. After eliminating firms which do not meet the required criteria (see section 4.2.2), a final sample of 2,970 firms (1,172 active firms, 1,773 dead firms and 25 suspended firms) is obtained. Financial accounting data pertaining to the old and new hypotheses (see table 4.2.3) is collected from DataStream for all 2,970 firms between 1988 and 2009. This results in a panel data of 32,363 firm-year observations. Data for 2,799 acquisition bids for UK public targets made between 1st July 1989 and 30th June 2011 is collected from Thomson OneBanker. The algorithm discussed in section 4.2.5 which employs the 'June approach' is used to match the data from OneBanker and DataStream to create a unique database, with suitably aligned data, to facilitate the model development process. The logit model is used as the base model for testing the hypotheses and for developing the takeover prediction model.

The issue of model stability across time and intertemporal variation of model parameters is discussed in section 4.3.5. The level of model stability will, perhaps, influence the choice of the optimal model estimation period (discussed in 4.4.3). The new model is evaluated by testing its ability to predict targets out-of-sample (predictive ability). Different portfolio selection techniques are used to ensure robustness of the results. The model's ability to generate abnormal returns for investors is also tested using the methodology discussed in section 4.5.

Overall, the focus of the methodology employed across the three empirical chapters of this study (chapters 5, 6 and 7) is to ensure that a robust process is followed both in the development and testing of the takeover prediction model. As discussed in chapter 2 (see sections 2.5 and 2.6), the results of several prior studies are, perhaps, affected by substantial methodological biases or shaped by the choice of methods. This study, therefore, contributes to the literature by providing a more robust and comprehensive test of old prediction hypotheses as well as by introducing (and evaluating) several new hypotheses for takeover prediction.

CHAPTER 5 HYPOTHESES VALIDATION

5.1 Overview

The objective of this chapter is to test and validate both the old and the new hypotheses discussed in chapter 4. These hypotheses (and associated proxies) are combined to develop the new model which is evaluated in chapter 6. In this chapter, the empirical tests are conducted using the unbalanced panel data set. The process of eliminating outliers from the dataset is discussed in section 4.2.6. The final dataset is analysed using the univariate and multivariate techniques discussed in section 4.3. The old hypotheses are evaluated in section 5.2 and the new hypotheses are evaluated in section 5.3. The impact of the chosen data winsorisation procedure is evaluated in section 5.4. Tests for model stability and intertemporal variation in model parameters are conducted in section 5.5.

5.2 Hypotheses evaluation: Old hypotheses

5.2.1 Overview

The old hypotheses discussed in the study are tested using the full sample. This retest is important given the differences between the sample design and methodology in this study and those employed in prior studies. The key sampling and methodological differences between this study and prior studies are discussed in section 2.6.3 and section 4.2.3. The old hypotheses discussed here include: the inefficient management, firm undervaluation, growth-resource mismatch, industry disturbance, firm size, free cash flow, tangible property and firm age hypotheses. The multivariate model is a logit regression model which generates parameter estimates through the maximum likelihood method. The analyses are conducted using the RATS econometrics software and p-values are computed from heteroscedasticity-consistent (or Huber-White) standard errors. The descriptive statistics obtained after adjusting for outliers (as discussed in section 4.2.6) are presented in table 5.2.1.

Table 5.2.1: Descriptive Statistics for proxies of management inefficiency, firm undervaluation and growth-resource mismatch

Hypothesis			N Valid	Mean	Mean Diff. (Sig)	MWU U (Sig.)	Std. Dev	Skewness	Min	Max	25th Percentile	Median	Median Diff. (Sig)	75th Percentile
Inefficient management	Profitability	0	30,728	0.084			0.286	-0.860	-0.653	0.598	-0.003	0.118		0.232
		1	1,635	0.114	-0.030***	**	0.235	-0.889	-0.653	0.598	0.040	0.151	-0.033	0.219
	ADAR	0	24,232	0.0001			0.003	0.831	-0.035	0.060	-0.001	0.0001		0.001
		1	1,635	-0.0004	0.0005***	***	0.003	-0.835	-0.017	0.013	-0.002	-0.0001	0.0002***	0.001
Under Valuation	BTM	0	26,045	0.493			0.582	0.908	-0.440	1.986	0.123	0.372		0.751
		1	1,541	0.468	0.025*		0.536	0.760	-0.440	1.986	0.128	0.379	-0.007	0.754
	Positive BTM	0	26,045	0.530			0.536	1.293	0.000	1.986	0.123	0.372		0.751
		1	1,541	0.507	0.023*		0.487	1.211	0.000	1.986	0.128	0.379	-0.007	0.754
Growth resource mismatch	Sales growth	0	26,893	0.183			0.395	1.590	-0.386	1.379	-0.026	0.090		0.266
		1	1,566	0.172	0.011		0.367	1.843	-0.386	1.379	-0.014	0.082	0.008**	0.235
	Liquidity	0	30,708	0.151			0.178	1.560	0.000	0.656	0.023	0.082		0.205
		1	1,635	0.119	0.032***	***	0.146	2.000	0.000	0.656	0.020	0.067	0.015***	0.154
	Leverage	0	30,714	0.490			0.655	1.987	0.000	2.689	0.016	0.263		0.651
		1	1,634	0.566	-0.076***	***	0.674	1.812	0.000	2.689	0.068	0.365	-0.102***	0.740

Notes: The table presents the descriptive statistics for key variables and compares the results for targets to those of non-targets. The hypotheses and their proxies are shown in the first two columns. Profitability is the ratio of EBITDA to total capital employed, ADAR is the average daily abnormal return, book to market is the ratio of book value of equity to market value of equity, Positive BTM presents statistics for book to market ratio by winsorising all observations with negative book to market ratios at 0 (i.e., replacing negative BTM ratios with 0), Sales growth is the rate of change in total revenues from the previous period, Liquidity is the ratio of cash and short term investments to total assets and Leverage is the firm's debt to equity ratio. In the third column, '0' indicates the results for non-targets and '1' indicates the results for targets. Mean difference for each variable is the difference between the mean for non-targets and targets prior to rounding-up. MWU (U-test) generates the U statistic and the level of significance of U. U (sig) shows the U statistic obtained (and the level of significance of U) when testing whether there is a difference in the distribution of a variable for targets and non-targets. The Median Diff (sig.) shows the difference in median between targets and non-targets for each variable (and its level of significance). *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 5.2.1 cont'd: Descriptive statistics for proxies of asymmetric valuation, firm size, free cash flow, tangible assets, firm age and financial distress

Hypothesis			N Valid	Mean	Mean Diff.	MWU U	Std. Dev.	Skewness	Min	Max	25th Percentile	Median	Median Diff.	75th Percentile
Asymmetric	Residual	0	24,232	0.017			0.017	4.481	0.000	0.059	0.006	0.013		0.023
valuation	volatility	1	1,174	0.017	0.001		0.015	1.786	0.000	0.059	0.004	0.014	-0.001**	0.023
Firm	Ln	0	30,719	17.682			2.237	0.210	6.908	25.976	16.218	17.493		18.991
size	assets	1	1,635	18.169	-0.486***	***	1.795	0.493	12.528	24.029	16.868	17.983	-0.490***	19.195
Tangible	PPE/TA	0	30,471	0.309			0.249	0.002	0.002	0.863	0.093	0.264		0.460
property		1	1,634	0.339	-0.030***	***	0.259	0.002	0.002	0.863	0.111	0.294	-0.030***	0.513
FCF	FCF/TA	0	23,693	-0.042			0.184	-1.461	-0.553	0.187	-0.090	0.008		0.071
		1	1,467	0.000	-0.042***	***	0.134	-1.758	-0.553	0.187	-0.044	0.023	-0.015***	0.078
Payroll	HR cost	0	22,234	0.341			0.271	1.779	0.057	1.166	0.165	0.265		0.405
synergies	to sales	1	1,338	0.314	0.027***		0.225	1.942	0.057	1.166	0.168	0.257	0.008	0.381
Firm	Age	0	28,334	31.874			32.618	1.048	0.000	163.000	6.000	17.000		54.000
age		1	1,552	30.760	1.114		31.711	1.204	0.000	164.000	7.000	16.000	1.000*	49.000
Financial	ZSCORE	0	25,877	29.909			66.563	2.851	-17.593	273.926	2.076	8.212		20.499
Distress		1	1,459	25.954	3.955**	**	60.249	3.221	-17.593	273.926	2.195	7.434	0.778***	16.834

Notes: The table presents the descriptive statistics for key variables and compares the results for targets to those of non-targets. The hypotheses and their proxies are shown in the first two columns. Residual volatility (a proxy of the asymmetric valuation hypothesis) is computed from the firm's one-year daily abnormal returns, Ln assets is the natural log of the firm's total assets, PPE/TA is the ratio of tangible assets (property, plant and equipment) to total assets, FCF/TA is the ratio of free cash flow (operating cash flow less capital investments) to total assets, HR cost to sales is the ratio of payroll expenses to total revenue, Age is the number of years since incorporation and ZSCORE is the firm's Taffler Z score. In the third column, '0' indicates the results for non-targets and '1' indicates the results for targets. Mean difference for each variable is the difference between the mean for non-targets and targets prior to rounding-up. MWU (U-test) generates the U statistic and the level of significance of U. U (sig) shows the U statistic obtained (and the level of significance of U) when testing whether there is a difference in the distribution of a variable for targets and non-targets. The Median Diff (sig.) shows the difference in median between targets and non-targets for each variable (and its level of significance). *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 5.2.1 compares the descriptive statistics (including, mean, standard deviation, skewness, minimum, maximum, and quartiles) for each firm-level hypothesis (and proxy) for targets (denoted by '1') and non-targets (denoted by '0'). The results of the descriptive statistics presented in table 5.2.1 are further discussed in sections 5.2.2 to 5.2.9 and 5.3.7 to 5.3.9. The outlier elimination process is fully discussed in section 4.2.6 (chapter 4). The process involved winsorisation of key variables at the 5^{th} and 95^{th} percentile. This process has substantially reduced the level of skewness in the distribution of the variables and has eliminated implausible values. It is worth acknowledging that, while steps have been taken to eliminate extreme values, their presence does not necessarily pose any problems to the multivariate analysis as the base model (i.e., the logit probability model) does not assume that the independent variables are normally distributed (Cox (1970), Press and Wilson (1978) and Lo (1986)). The fact that the logit estimator maintains its consistency irrespective of the distributional characteristics of the independent variable has remained its main strength (Lo (1986)).

In addition to the univariate analysis (results to be further discussed in sections 5.2.2 to 5.2.9), different logit regression models are run. The general model is specified in equation 4.3.4(1) and restated below.

$$Logit(P_i) = \beta_0 + \beta_1 X_{1,i} + \cdots + \beta_m X_{m,i} \dots \dots \dots Eqn\ 4.3.4(1)$$

Here, X is the hypothesis (proxy) to be tested and β is the parameter estimate from the logit regression analysis. The results from this analysis are presented in table 5.2.1b.

In table 5.2.1b, model 1A is a univariate logit regression model with no control variables. The values reported in the table represent the coefficients (and their statistical significance) obtained by regressing each independent variable (old hypothesis and proxy) against the dependent variable (takeover probability). Model 1B, 1C and 1D are multivariate logit regression models. Model 1B combines all 'old' hypotheses (proxies) as model independent variables. No industry dummies are added to model 1B. Model 1C uses all the old variables as well as the LMDummy and NBVDummy. Their relevance is discussed in section 3.3.2 and section 3.3.3. As in model 1B, no industry dummies are added to model 1C. Model 1D is similar to model 1C but also includes industry dummies to control for industry effects.

Table 5.2.1b: Pooled regression results for existing hypotheses
Panel A: Robust (Huber-White) Standard errors

Hypotheses	Proxies	Model 1A	Model 1B	Model 1C	Model 1D
Inefficient	Profitability (-)	0.395***	0.060	-0.268	-0.270
Management	LMDummy (+/-)	-0.424***	-	-0.272*	-0.268*
	ADAR (-)	-70.488***	-83.317***	-83.350***	-82.160***
Undervaluation	BTM (+)	-0.076*	-0.120*	-0.206***	-0.176**
	NBVDummy (+/-)	0.023	-	-0.220**	-0.236**
Growth-resource	Sales Growth (+/-)	-0.074	-0.074	-0.079	-0.082
Mismatch	Liquidity (+/-)	-1.216***	-0.605**	-0.638**	-0.602**
	Leverage (+/-)	0.161***	0.043	0.054	0.052
	GRDummy (+)	0.026	-0.030	-0.036	-0.045
Industry Dist.	IDUMMY (+)	-0.097	-0.008	0.000	-0.021
Firm Size	Ln Assets (-)	0.094***	0.040**	0.035**	0.043**
Free Cash Flow	FCF (+)	1.539***	0.908***	0.886***	0.857***
Tangible assets	PPP/TA (+)	0.463***	0.520***	0.455***	0.403**
Firm Age	Age (-)	-0.001	-0.003***	-0.003***	-0.003***
Constant Term			-3.506***	-3.229***	-3.472***
Industry dummies		NO	NO	NO	YES
Usable Observations			16,854	16,854	16,854
Deviance (–2LL)			7,206	7,202	7,193
Pseudo-R^2			0.006	0.007	0.008
LR Test of Coefficients			105.550***	113.290***	132.045***

Panel B: Roger standard errors (adjusted for firm, year and industry clustering)

Hypotheses	Proxies	Model 1E (firm)	Model 1F (Year)	Model 1G (Industry)
Inefficient	Profitability (-)	-0.268	-0.268	-0.268
Management	LMDummy (+/-)	-0.272*	-0.272**	-0.272
	ADAR (-)	-83.350***	-83.350**	-83.350**
Undervaluation	BTM (+)	-0.206***	-0.206***	-0.206***
	NBVDummy (+/-)	-0.220*	-0.220*	-0.220**
Growth-resource	Sales Growth (+/-)	-0.079	-0.079	-0.079
Mismatch	Liquidity (+/-)	-0.638**	-0.638**	-0.638**
	Leverage (+/-)	0.054	0.054	0.054
	GRDummy (+)	-0.036	-0.036	-0.036
Industry Dist.	IDUMMY (+)	0.000	0.000	0.000
Firm Size	Ln Assets (-)	0.035*	0.035*	0.035***
Free Cash Flow	FCF (+)	0.886***	0.886***	0.886***
Tangible assets	PPP/TA (+)	0.455***	0.455***	0.455**
Firm Age	Age (-)	-0.003***	-0.003**	-0.003**
Constant Term		-3.229***	-3.229***	-3.229***
Usable Observations		16,854	16,854	16,854
Deviance (–2LL)		7,146	7,144	7,146
Pseudo-R^2		0.016	0.016	0.016
LR Test of Coefficients		98.94***	440.16***	98.94***

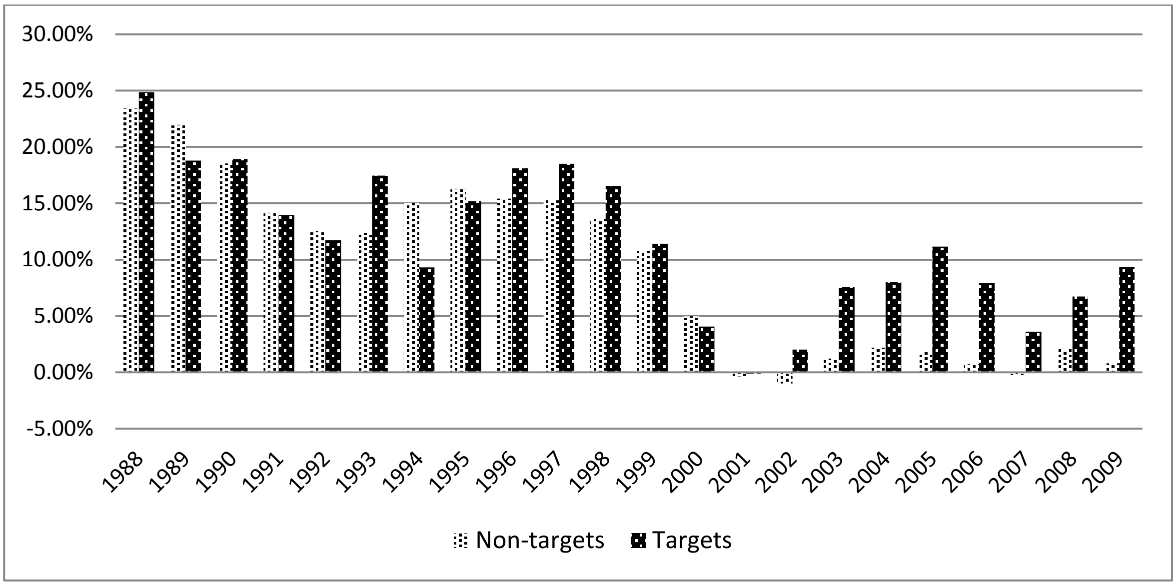
Notes: The table presents the results of logit regression analysis where the dependent variable is takeover probability (bivariate) and the independent variable are the old prediction hypotheses. The hypothesis being tested is shown in the first column and its associated proxy is shown in the second column. Profitability is the ratio of EBITDA to total capital employed. LMDummy takes a value of 1 when a firm makes a loss in a given year and a value of 0 otherwise. ADAR is the average daily abnormal return. Book to market (BTM) is the ratio of book value of equity to market value of equity. NBVDummy takes a value of 1 when the BTM is negative and a value of 0 otherwise. Sales growth is the rate of change in total revenues from the previous period. Liquidity is the ratio of cash and short term investments to total assets. Leverage is the firm's debt to equity ratio. GRDummy takes a value of 1 when there is a mismatch between a firm's growth opportunities and its resources and a value of 0 otherwise. IDummy takes a value of 1 if a takeover occurs in a firm's industry and a value of 0 otherwise. Ln Total Assets is the natural log of the firm's total assets. FCF/TA is the ratio of free cash flow (operating cash flow less capital investments) to total assets. PPE/TA is the ratio of tangible assets (property, plant and equipment) to total assets. Age is the number of years since incorporation. The hypothesised sign is shown in brackets (e.g., (+), (-)). Model 1A represents univariate logit regression models where the dependent variable is takeover probability and the sole independent variable is the variable in question (proxy). For example the coefficients of profitability (a proxy for management inefficiency) are obtained from regressing profitability as the sole independent variable with takeover probability as the binary dependent variable (with no control variables). Model 1B is a multivariate logit model which uses all the old variables as independent variables and regresses them on firm takeover probability. Model 1C is a multivariate logit model which uses all the old variables (including LMDummy and NBVDummy) as independent variables and regresses them on firm takeover probability. Model 1D replicates model 1C but adds industry dummies. Industry classifications are discussed in table 4.2.2. Panel B presents results obtained when standard errors are computed using the Rogers (1993) methodology of adjusting robust standard errors for correlation across different clusters (firm, years and industry). 'Usable observations' is size of the sample used in the analysis, deviance is the -2 log likelihood ratio of the model and the test of model coefficient is the Chi Square test. *, **, and *** indicate significance at the 10%, 5% and 1% levels.

Models 1E, 1F and 1G (panel B) are similar to model 1C but the standard errors in the three models are corrected for firm, year and industry clustering, respectively, following the Rogers (1993) methodology. The results from panel A and B show are generally consistent. This indicates that correcting for clustering across firms, years and industries does not materially change the conclusions. The results from models 1A to 1G (panels A and B) are discussed in sections 5.2.2 to sections 5.2.9.

5.2.2 Inefficient management hypothesis

The inefficient management hypothesis (as discussed in section 3.2.2) predicts that takeover likelihood decreases with firm performance i.e., poorly managed firms are more likely to be takeover targets. Different variables including profitability (the return on capital employed) and 1-year average daily abnormal returns (ADAR) are used to proxy for management performance. A dummy variable (LMDummy) is also used to directly test whether loss-making firms are more likely to receive takeover bids. Figure 5.2.2 plots the variations in average profitability for targets and non-targets for the period 1988-2009.

Figure 5.2.2 Variations in average profitability for UK targets and non-targets



Notes: Figure 5.2.2 plots the variations in average profitability (measured as the ratio of EBITDA to capital employed) for targets and non-targets for the period 1988 to 2009. The chart shows that, post 1996, targets have achieved higher profitability year-on-year when compared to non-targets.

There is no discernable trend in the profitability of targets and non-targets between 1988 and 1995. Over this period, I find that targets report higher profits in 3 out of 8 years. Post 1995, there is a clear tendency for targets to generate higher average annual profits when compared to non-targets. Indeed, targets generate comparatively higher profits in 14 out of 14 years between 1996 and 2009. The results shown in table 5.2.1 (panel A) suggest that targets are more profitable than non-targets, on average. The average profitability (proxied by the ratio of EBITDA to capital employed) of UK non-targets (targets) is 8.40% (11.40%). The difference in mean profit margin between the two samples is –3.00pp (percentage points) significant at the 1% level. The results are again corroborated by median values. The median values show that UK targets are more profitable than non-targets. The median profitability is 15.10% for targets and 11.8% for non-targets, yielding a difference of 3.30pp (insignificant at the 10% level). The results from the U-test also show that the distribution of profitability for targets and non-targets is integrally different at a 5% significance level. The finding is consistent with Palepu (1986) and Barnes (1998) who report that takeover likelihood increases with accounting profitability (measured by return on equity and operating margin, respectively).

The picture painted above is somewhat reversed when management efficiency is measured from the market's perspective by using stock performance (proxied by ADAR – average daily abnormal return in the 260 days to June 30th). The results (shown in table 5.2.1) indicate that targets perform worse than non-targets in the year prior to the bid announcement. Targets have an ADAR of –0.004% while non-targets have an ADAR of 0.001% in the one-year period to 30 June prior to the period in which they receive a bid. The difference in means of 0.005pp is significant at the 1% level. These findings are corroborated by the median and percentile values, as well as, the results from the U-test. The results are also consistent with Palepu's finding that targets earn significant negative abnormal returns prior to takeover bids (Palepu (1986)).

The results from the univariate analysis (discussed above) are replicated in the multivariate analysis (models 1A, 1B, 1C and 1D in table 5.2.1b). Models 1A and 1B suggest the existence of a significantly negative relationship between ADAR and takeover likelihood and a positive relationship between accounting profitability and takeover likelihood. The coefficient of profitability is positive and significant in model 1A – univariate regression model – but loses significance when other determinants of takeover probability are controlled for. This would seem to suggest that firms with higher profitability are more likely to receive takeover bids. However, when the LMDummy[150] is added to the regression, the sign of the profitability variable changes and becomes negative. This suggests that within the sample of profitable firms (i.e., for all profitable firms), firms with lower profitability are more likely to be takeover targets. The results from models 1A, 1C and 1D confirm that loss-making firms are less likely to be takeover targets as takeover probability is negatively related to the LMDummy variable (statistically significant at the 1% level). The results in model 1C are robust to clustering across firms, years and industries (as shown in models 1E, 1F and 1G). Put together, these results suggest that, all else equal, targets tend to be profit-making firms which experience a decline in their

[150] The dummy variable takes a value of 1 when a firm makes a loss and a value of 0, otherwise.

ADAR over the past year[151]. Overall, the results suggest that profitable firms lacking future growth opportunities (as proxied by abnormal stock returns) constitute attractive targets for bidders.

While prior studies argue that targets are generally characterised by inefficient management (Palepu (1986), Powell (1997), Barnes (2000), Espahbodi and Espahbodi (2003), and Brar et al. (2009)), there has been no clear qualification of 'management inefficiency'. Different measures of management inefficiency have been used across studies, with a number of studies reporting inconsistencies between accounting measures of performance, market measures of performance and takeover likelihood (see, for example, Palepu (1986), Powell (1997), Barnes (1998) and Espahbodi and Espahbodi (2003))[152]. This study perhaps sheds some light by highlighting the differences between the two types of performance measures and their effects on takeover probability.

5.2.3 Undervaluation hypothesis

The undervaluation hypothesis (discussed in section 3.2.3) predicts that firms that are, potentially, undervalued (as proxied by book to market (BTM) ratios) are likely to have a higher takeover likelihood[153]. As discussed in section 3.3.2, the book value of equity to market value of equity (BTM) ratio is used as a proxy of firm valuation. The results on the difference in BTM ratios between targets and non-targets are fairly mixed when year-on-year results are examined. Figure 5.2.3 shows that targets have a substantially higher mean BTM ratio in several years (including 1988, 1989, 1992, 1994, 1999, 2000, 2001 and 2003). The average BTM ratio of targets and non-targets are indifferent in 1995, 1998, 2002 and 2004. Non-targets have a substantially higher mean BTM ratio in 1990, 1991, 1993, 1996, 1997, 2005, 2006, 2008 and 2009.

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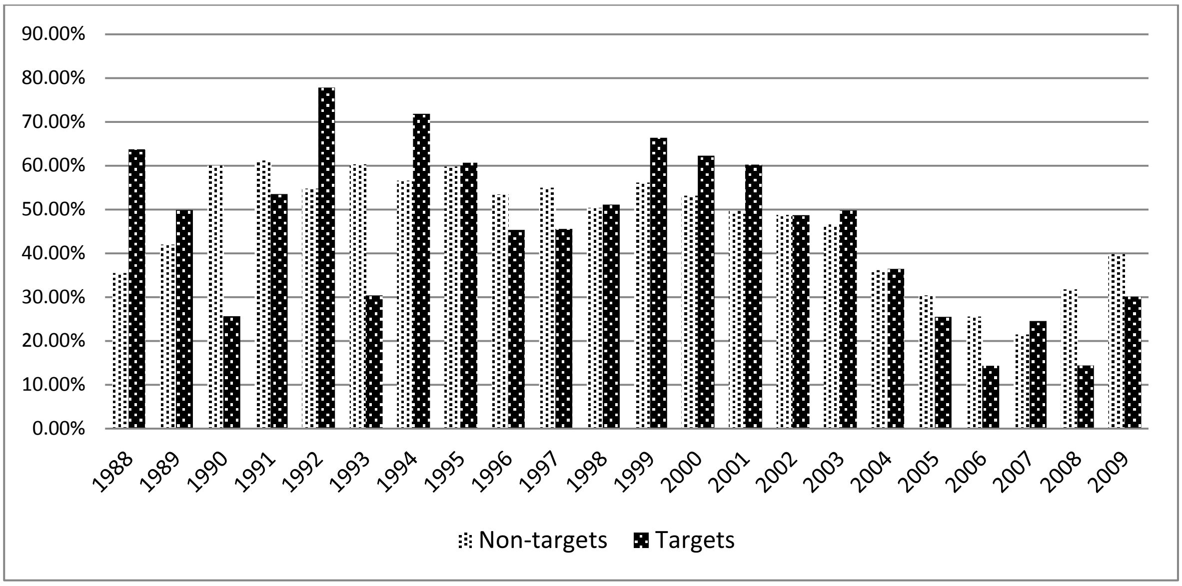
151 Evidence from the negative relationship between sales growth and takeover probability (see table 5.2.1 panel A and table 5.2.1b) also support the contention that takeover targets are profitable firms with declining opportunities for future growth (or poor future prospects).

152 Palepu (1986) and Barnes (1998), for example, find that, contrary to the inefficient management hypothesis (and their qualification of management inefficiency), the relationship between takeover likelihood and profitability is positive.

153 All else equal, undervalued firms (as discussed in section 3.3.3) are likely to have a higher BTM, a higher ETP and higher dividend yield, when compared with the population of firms.

Figure 5.2.3: Variations in BTM ratios for UK targets and non-targets



Note: Figure 5.2.2 shows the variation in average book to market (BTM) ratios of UK firms from 1988 to 2009. Firms with higher BTM ratios are perceived to be comparatively undervalued, and hypothesised to be more susceptible to takeover bids (see section 3.2.3). It is therefore expected that targets will have higher BTM ratios when compared to non-targets. The results show a mixed picture from one year to the other.

The results from univariate analysis (table 5.2.1) show that, overall, targets have a lower mean BTM ratio. The mean BTM ratio of targets and non-targets is 46.80% and 49.30% respectively. These results suggest that on average, targets are not undervalued when compared to non-targets. The difference in mean BTM ratios of 2.50pp is significant at the 10% level. The results do not provide support for the undervaluation hypothesis. The median BTM ratio for targets and non-targets is 37.90% and 37.20% respectively. The difference in median is nonetheless, not statistically significant. The results reported above do not change even when observations with negative book values are winsorised at 0.00%.
Again, the results from the multivariate analyses do not support the undervaluation hypothesis. Model 1A shows that takeover probability is negatively related to the BTM ratio. The negative relationship persists as other determinants of takeover likelihood are controlled for (see model 1B, 1C and 1D). As shown in models 1E, 1F and 1G, these results are robust to clustering across firms, years and industries. On a whole the results suggest that contrary to the hypothesis, firms with low BTM values have a higher takeover likelihood.

The finding that the undervaluation hypothesis is not supported in a UK sample is consistent with other UK studies including Powell (1997, 2004) and Powell and Yawson (2007). Powell and Yawson (2007), for example, find no significant relationship between a firm's market to book value and its takeover likelihood. The proxy for undervaluation (BTM ratio) used in this study is similar (but the inverse) to the proxy (MTB ratio) used in most prior studies in takeover prediction including (Palepu (1986), Ambrose and Megginson (1992), Powell (1997, 2001, 2004), Powell and Yawson (2007), Cremers et al (2009) and Brar et al. (2009)). To my knowledge, no study in takeover prediction has applied an alternative proxy. It is worth reiterating that while this measure (BTM or MTB) of undervaluation has been extensively used in the literature, it is, perhaps, inadequate (and a limitation of the study) as discussed in section 3.2.4. There are therefore opportunities for further research to explore the suitability of alternative and improved proxies for undervaluation.

5.2.4 Industry disturbance hypothesis

The industry disturbance hypothesis (discussed in section 3.2.4) argues that the likelihood of takeovers within an industry will increase with the announcement of a merger bid in that industry in the same year. The sample is made up of 1,635 takeover bids (made between July 1989 and June 2011) of which 332 (20.31%) bids occur in 'disturbed' industries[154]. Contrary to the hypothesis, the multivariate analysis shows that the industry disturbance dummy variable (IDummy) has a negative (though statistically insignificant) relationship with takeover probability. The results do not support the contention that firms in takeover-active industries are more likely to receive a bid than others. The relationship is statistically insignificant across all four models (1A, 1B, 1C and 1D).

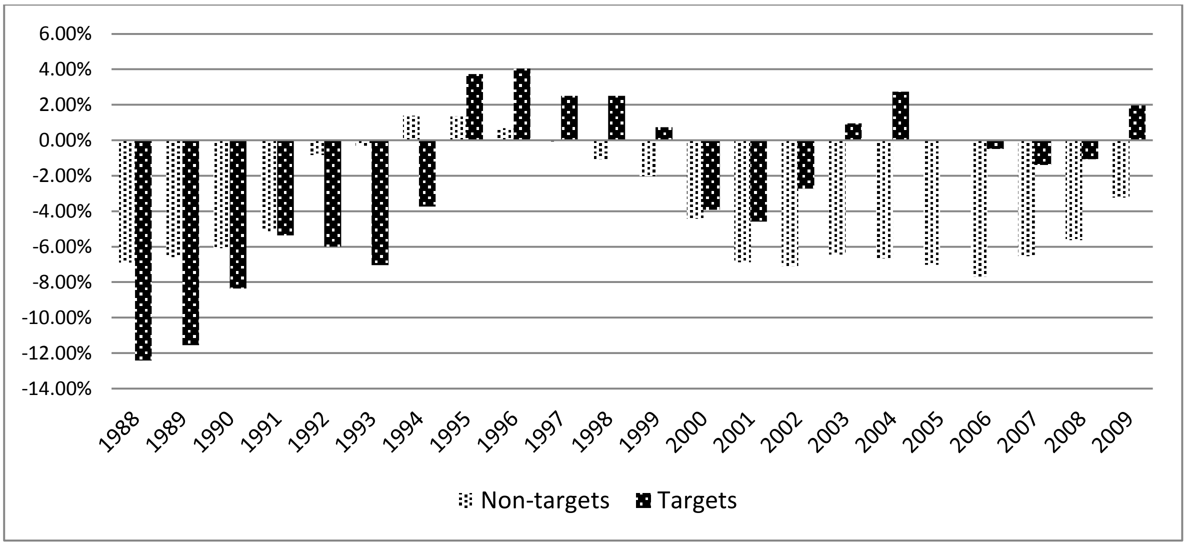
In comparison with prior research, Palepu (1986) finds that, contrary to the hypothesis, the likelihood of takeovers decreased when a takeover is completed in the industry. Other researchers (such as Barnes (1998), Powell (2004), Brar et al. (2009) and Ouzounis et al. (2010)) do not find the hypothesis relevant for inclusion in target prediction models. One reason for this non-significance could be that, the proxy (IDummy) is a poor measure of disturbance given the high-frequency of takeovers within the UK and US contexts. Depending on the dynamics and concentration of the industry, one or a few takeovers might not be sufficient to stimulate a restructuring response from other firms within the industry. Further, the industry classification system used in this study – which employs 12 industry groups – is, perhaps, too broad to capture the effects of any disturbance caused by a completed merger.

[154] That is, 20.31% of bids in the sample occur in industries where other bids have been announced.

5.2.5 Free cash flow hypothesis

The free cash flow hypothesis (discussed in section 3.2.5) predicts that targets should have significantly higher levels of free cash flow to asset ratio (FCF) compared to non-targets. The results from table 5.2.1 show that targets have higher levels of FCF compared to non-targets. Targets have a mean FCF of about 0.00% of their total assets (i.e., no free cash flow) while non-targets have a mean FCF equivalent to –4.20% of their total assets (i.e., net cash outflow of 4.20% of their total assets). The difference in mean FCF between targets and non-targets (4.2pp) is statistically significant at a 1% level. The U-test also confirms the significant difference in the distribution of the FCF variable between targets and non-targets. These results are further supported by values obtained for the 25th, 50th and 75th percentile on FCF for targets and non-targets. The median FCF for non-targets and targets are 0.80% and 2.30% respectively. The difference in median FCF of 1.5pp is statistically significant at the 1% level. The results are partly consistent with Powell and Yawson (2007) who report that UK targets have an average FCF of 1.53% while firms which were not engaged in any restructuring activities (layoffs, divestitures and bankruptcy) had a lower average FCF of 0.93%. The results reported by Powell and Yawson (2007) are slightly higher than those in this study. This is because their study covers the period 1992-2002 (during which UK firms recorded high free cash flows – see figure 5.2.5), while the current study covers the period 1988-2009.

Figure 5.2.5: Variations in free cash flow ratios for UK targets and non-targets



Notes: Figure 5.2.5 plots the average free cash flow to total assets (FCF/TA) ratio for UK targets and non-targets between 1988 and 2009. Free cash flow is computed as operating cash flow less capital expenditures. IAS 7 – Cash flow statements was only issued by the IASB in December 1992 (effective 1 January 1994) explaining why FCF/TA was significantly lower prior to this date. Post FYE 1995, it targets have a higher average FCF/TA when compared to non-targets.

Figure 5.2.5 shows the variation of the FCF/TA ratio of UK firms over the period 1988 – 2009. The extreme negative values in the early years are, perhaps, due to the fact that IAS – 9 (issued in December 1992) only came into effect on 1 January 1994 (Alexander et al. (2007)). Figure 5.2.5 supports the conclusion from the univariate analysis. It shows that from FYE 2005 onwards, targets report higher (more positive or less negative) average free cash flows than non-targets in every year.

In line with the results from the univariate analysis, the results from the multivariate analysis provide support for the FCF hypothesis. As hypothesised (section 3.3.5), the availability of FCF increases a firm's likelihood of receiving a bid as shown in models 1A, 1B, 1C and 1D. The coefficient of the FCF variable is significant at the 1% level across all four models. The results remain robust when the standard errors are adjusted for clustering (as in models 1E, 1F and 1G) following Rogers (1993). The results support the findings of prior studies (e.g., Powell (1997) and Brar et al. (2009)) showing that firms with free cash flow attract takeover bids.

5.2.6 Growth-resource mismatch hypothesis

The growth-resource mismatch hypothesis (discussed in section 3.2.6) predicts that firms with a mismatch between their resources and their growth opportunities are likely to have a higher takeover likelihood. The key proxy for the mismatch between growth opportunities and firm resources is the growth-resource dummy (GRDummy) which is computed from three variables – sales growth, liquidity and leverage. The derivation of this proxy from the three variables is discussed in section 3.3.6. The three composite variables cannot be fully interpreted in the growth-resource context through univariate analysis. Their descriptive statistics are, nonetheless, discussed below.

Table 5.2.1 shows that targets have lower levels of sales growth compared to non-targets as indicated by the mean, median, 25th and 75th percentile for sales growth. The mean sales growth for targets is 17.20% as against 18.30% for non-targets. The difference in sales growth (of 1.1 pp) is not statistically significant. The result from the U-test also confirms that the distribution of sales growth for targets and non-targets are not statistically different. The median test shows a statistically significant difference of 1.0% in the median sales growth for targets (8.2%) and non-targets (9.2%). The difference (0.8pp) is significant at the 5% level. These results suggest that targets perhaps experience poor growth in sales prior to bid announcements.

Consistent with Espahbodi and Espahbodi (2003) and Palepu (1986), targets have comparatively lower levels of liquidity. On average, cash and near cash resources constitute 11.9% of the total assets of targets, as against 15.1% for non-targets. The difference in mean liquidity between targets and non-targets (of 3.2 pp) is significant at the 1% level. The median and quartile values further reinforce this finding. The U-test further confirms a significant difference in the distribution of the liquidity measure for targets and non-targets. The median liquidity level for targets is 6.70% as against 8.20% for non-targets. The difference (1.5pp) is also significant at the 1% level.

Contrary to Palepu (1986) but consistent with Espahbodi and Espahbodi (2003), targets are significantly more levered than non-targets. Targets have a mean leverage of 56.60% as against 49.00% for non-targets. The difference in mean leverage (of 7.6pp) is statistically significant at the 1% level. The results from the 25th, 50th and 75th percentiles also show that targets are more levered than non-targets. The median leverage for targets (non-targets) is 36.50% (26.35%) and the difference in median (10.2pp) is significant at the 1% level. The U-test also confirms that the difference in leverage between targets and non-targets is statistically significant.

In summary, this preliminary evidence suggests that targets have lower liquidity and higher leverage on average when compared with non-targets. The implication is that targets generally require high resources to service their debt but suffer from a general lack of liquidity. These firms also appear to suffer a decline in sales in the year prior to receiving a bid. Further evidence can be drawn by looking at the proportion of firms with growth-resource mismatch that do (and do not) receive a takeover bid. Of the sample of 1,635 targets, 387 targets (or 23.67% of targets) experience a growth-resource mismatch prior to receiving a bid. Nonetheless, 24.46% of non-targets[155] experience a growth-resource mismatch but do not receive a bid. This suggests that a growth-resource mismatch does not, perhaps, increase a firm's takeover likelihood, on average. Further analysis is conducted using the multivariate framework.

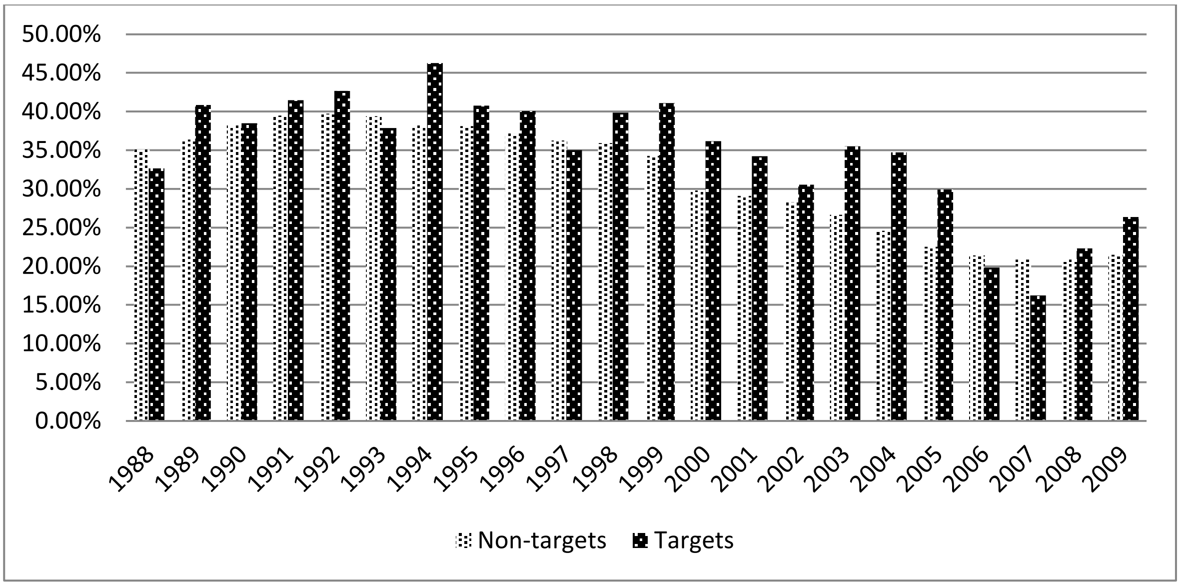
155 7,517 (of 30,729) non-targets also experience a growth-resource mismatch.

The results from the multivariate analysis (see models 1A, 1B, 1C and 1D, table 5.2.1b) show no support for the hypothesis. In line with Espahbodi and Espahbodi (2003) but contrary to Palepu (1986), the coefficient of the GRDummy variable is not statistically significant in any of the four models. Model 1A shows that takeover likelihood decreases with sales growth and liquidity but increases with leverage. The leverage variable loses its significance when other factors are controlled for in model 1B, 1C and 1D. The results do not support Palepu's (1986) finding that takeover probability is positively related with the GRDummy. In line with Espahbodi and Espahbodi (2003), the evidence suggests that the growth-resource mismatch hypothesis is either not supported or the GRDummy variable poorly operationalises the concept.

5.2.7 Tangible assets hypothesis

The tangible assets hypothesis (as discussed in section 3.2.7) predicts that takeover likelihood increases with the proportion of tangible fixed assets in a firm's portfolio. Figure 5.2.7 shows the variation in the level of tangible assets held by UK targets and non-targets for the period 1989-2009. The chart shows that, with the exception of 1988, 1993, 1997, 2006 and 2007, targets have higher levels of tangible assets when compared to non-targets.

Figure 5.2.7: Variations in the level of tangible assets held by UK targets and non-targets



Notes: Figure 5.2.7 shows the variation in the level of tangible assets (proxied as the ratio of property, plant and equipment to total assets) held by UK targets and non-targets for the period 1989-2009. The tangible assets hypothesis discussed in section 3.2.7 posits that targets are likely to have higher levels of tangible assets when compared to non-targets. In line with the hypothesis, the chart shows that targets have comparatively higher levels of tangible assets across several years.

In line with the hypothesis, the results from the univariate analysis (table 5.2.1) show that, overall, targets have substantially more tangible property than non-targets. On average, 30.9% of total assets in non-targets comprises of tangible assets while this figure is up to 33.9% for targets. The difference between tangible assets for targets and non-targets (3.00pp) is significant at the 1% level. The U-test also confirms the difference in the distribution of tangible assets between targets and non-targets. The results are further supported by the median and 75th percentile values. The median value for targets is 29.4% as opposed to 26.4% for non-targets. The difference in median (3.00pp) is significant at the 1% level. These results are consistent with prior empirical findings (e.g., Ambrose and Megginson (1992)). Ambrose and Megginson (1992), for example, find that US targets have a mean (median) real property ratio of 66.6% (63.6%) as opposed to non-targets with a mean (median) tangible assets ratio of 58.9% (52.3%)[156].

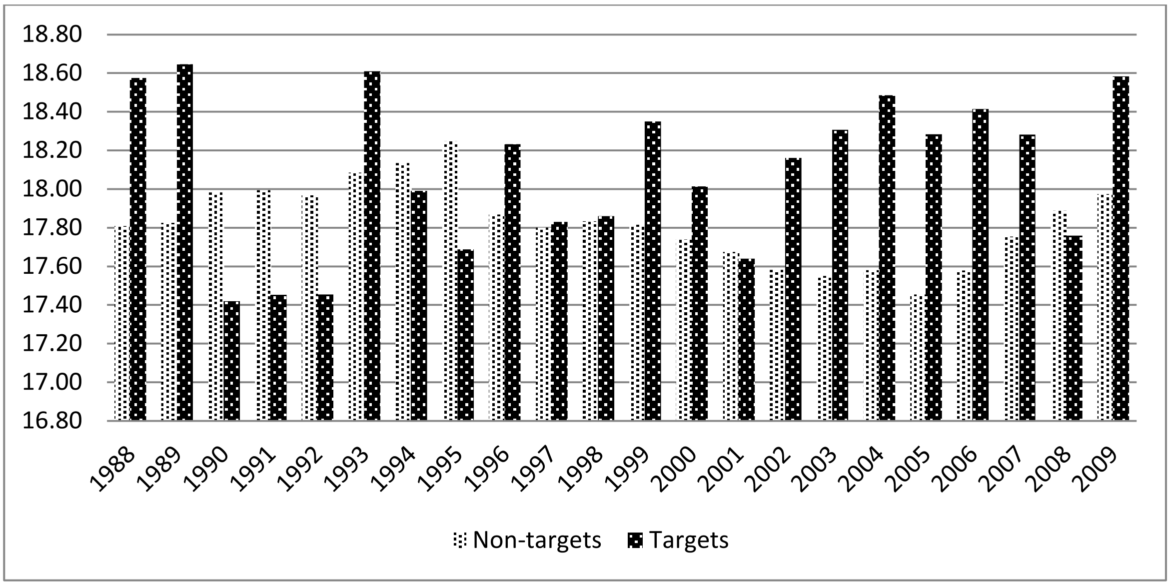
The results from the multivariate analyses further assert the validity of this hypothesis. Models 1A, 1B, 1C and 1D (in table 5.2.1b) show that the probability of receiving a bid increases with a firm's level of tangible assets. In all cases (models 1A, 1B, 1C and 1D), the coefficient of the tangible assets variable is statistically significant at the 1% level. The results are robust to industry differences as well as clustering (models 1E, 1F and 1G). As hypothesised, the presence of tangible property within a firm increases its likelihood of receiving a bid. These results are consistent with empirical findings reported in Ambrose and Megginson (1992) and Powell (2001).

5.2.8 Firm size hypothesis (old)

The (old) firm size hypothesis (discussed in section 3.2.8) predicts that takeover probability decreases with firm size for transaction cost reasons. This implies that, on average, non-targets should be comparatively larger firms when compared to targets. Contrary to this popular notion (see Palepu (1985), Ambrose and Megginson (1992), Barnes (1998), Powell (2004), Espahbodi and Espahbodi (2003) and Brar et al. (2009), amongst others), targets are marginally bigger than non-targets. As in prior research, firm size is measured as the natural log of total assets. Figure 5.2.8 shows the variation of target and non-target firm size from one year to another for the period 1988-2009. The chart shows that with the exception of 1990,1991,1992,1994, 1995 and 2008 targets, on average, are at least as large as non-targets across the period.

156 The difference in mean tangible assets for targets and non-targets is significant at the 0.05 level of significance.

Figure 5.2.8: Variations in the average firm size of UK targets and non-targets



Notes: Figure 5.2.8 shows the difference in firm size (expressed as log total assets) between targets and non-targets for the period 1988-2009. The old firm size hypothesis contends that non-targets are comparatively larger than targets. The figure shows that, on average, targets are indeed larger than non-targets across several years.

Targets in the sample have a mean firm size of 18.169 (equivalent to £77.75 million) while non-targets have a mean firm size of 17.682 (equivalent to £47.77 million). The results here are broadly in line with prior studies. Powell and Yawson (2007), for example, report that UK targets are significantly larger (in terms of total assets) when compared with firms not engaged in any restructuring activities (layoffs, divestitures and bankruptcies).

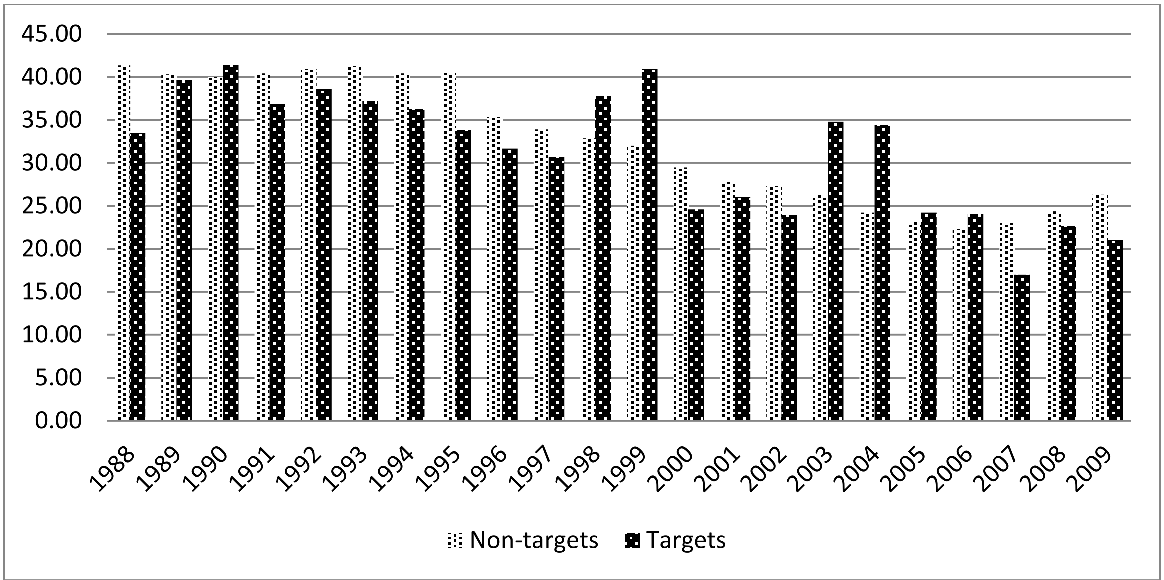
The difference in firm size between targets and non-targets (£29.97 million) is significant at the 1% level. The results obtained from the 25th, 50th and 75th percentiles reaffirm the finding that targets are not the smallest firms in the population. In line with Gibrat's Law (discussed in section 3.4.2), the level of skewness in the data is very low – the distribution of the natural log of firm size is approximately normally distributed. The results from the analysis of median also show that the median target has a firm size of 17.983 (equivalent to £64.55 million) which is significantly higher than the size of the median non-target (17.493 – equivalent to £39.55 million) at the 1% level.

Contrary to the predictions of the (old) firm size hypothesis, the multivariate analysis (see table 5.2.1b) finds a positive relationship between size and takeover probability. The simple logit model (model 1A) confirms the findings of the univariate analysis. This model shows that firm size has a positive relationship with takeover probability. The coefficient of firm size in model 1A is significant at the 1% level. The coefficient of firm size remains significant (at the 1% level) when other variables are controlled for (as in models 1B, 1C and 1D). These results are robust when standard errors are corrected for clustering across firm, years and industries (models 1E, 1F and 1G). These findings suggest that the hypothesised relationship between firm size and takeover probability (i.e., the old firm size hypothesis) is unsupported. In line with discussions in section 3.3.2, the new firm size hypothesis is tested in section 5.3.2. Overall, as will be further discussed in section 5.3.2, I find evidence that as hypothesised (i.e., the new firm size hypothesis), firm size has an inverse U-shaped relationship with takeover likelihood.

5.2.9 Firm age hypothesis

The firm age hypothesis (as discussed in section 3.2.9) predicts that takeover probability will decline with firm age implying that targets will be, perhaps, younger than non-targets, on average. Figure 5.2.9 plots the average age of UK targets and non-targets for the period 1988 to 2009.

Figure 5.2.9: Variations in the average age of UK targets and non-targets



Notes: figure 5.2.9 shows variations in the average age of target and non-target firms in the UK for the period 1989-2009. Age is measured as the number of years since the year of incorporation. The firm age hypothesis predicts that targets are comparatively younger firms. In support of the hypothesis, the chart shows that, on average, targets are comparatively younger than non-targets across several years.

The chart shows that targets are comparatively younger across several years. The main exceptions are 1998, 1999, 2003 and 2004 in which non-targets were younger than targets, on average. The results in table 5.2.1 (panel B) support the contention that targets are younger than non-targets, on average. The mean age of targets in the sample is 32.76 years as against 31.87 years for non-targets. The difference in mean age is not significant at a 10% level. The U-test also shows no support for the hypothesised relationship. The results from the median partly support the hypothesis. The median age of targets (of 16 years) is lower than the median age of non-targets (of 17 years). The median difference (of 1 year) is significant at the 10% level.

The hypothesis is supported by the multivariate analysis (table 5.2.1b). The results confirm that younger firms are highly susceptible to takeover bids. Models 1B, 1C and 1D show that, all else equal, the likelihood of receiving a bid decreases with firm age. The coefficient of the firm age variable is statistically significant at the 1% level (models 1B, 1C and 1D). As shown in models 1E, 1F and 1G, these results are robust to the clustering of standard errors across firms, years and industries. Brar et al. (2009) noted the possibility of a negative relationship between firm age and takeover probability but did not test such a relationship empirically. These results therefore provide some empirical support to Brar et al.'s (2009) contention on firm age. The findings also support prior empirical evidence (e.g., Hopenhayn (1992), Pakes and Ericson (1998) and Bhattacharjee et al. (2009)) suggesting that the probability of firm exit (through bankruptcies or takeovers) is negatively related to age.

This study introduces a firm lifecycle hypothesis which builds on the firm age hypothesis. While younger firms are likely to be more susceptible to takeovers, the literature suggests that old firms (with assets trapped within outdated structures) might also be revitalised through takeovers (Loderer et al. (2009)). This expansion of the firm age hypothesis is investigated in section 5.3.5.

5.2.10 Summary

Section 5.2 evaluates the empirical validity of the old prediction hypotheses. Consistent with the management inefficiency hypothesis, takeover likelihood increases with market underperformance. In line with the qualification of management inefficiency discussed in section 3.2.2, takeover likelihood increases with accounting performance but declines with market performance, all else equal. Contrary to the undervaluation hypotheses, on average, targets report lower BTM ratios when compared to non-targets. The multivariate analysis also shows a negative relationship between BTM and takeover probability.

The univariate and multivariate analysis support the free cash flow (FCF) and the tangible assets hypotheses – takeover probability increases with firm free cash flow and tangible assets, respectively. The relationship between firm age and takeover likelihood is supported by multivariate analysis (but not by the univariate analyses). In line with the firm age hypothesis, on average, targets are younger than non-targets. The mean age of targets in the sample is 30.76 years as against 31.87 years for non-targets. The multivariate analysis shows no support for the industry disturbance and growth-resource mismatch hypotheses. While 23.67% of targets experience a growth-resource mismatch prior to receiving a bid, 24.46% of firms which experience a growth-resource mismatch do not receive a bid. Contrary to the (old) firm size hypothesis, the results show no support for the contention that targets are small firms.

Overall, the results suggest that several of the old hypotheses (including the undervaluation, industry disturbance, growth-resource mismatch and firm size hypotheses) are not supported by the empirical evidence. The only hypotheses which are empirically supported are the inefficient management, firm age, free cash flow and tangible assets hypotheses. Perhaps, some of the proxies used to measure firm undervaluation, growth-resource mismatch and industry disturbance are inadequate (further discussed in sections 5.2.3, 5.2.4 and 5.2.6). The next section evaluates the empirical validity of the new takeover prediction hypotheses.

5.3 Hypotheses evaluation: New hypotheses

5.3.1 Overview

This study proposes several 'new' prediction variables which could, potentially, improve the success rates in takeover prediction. Some of these variables are drawn from other areas of M&A research but have not been employed in takeover prediction to date. The 'newness' in other variables is the fact that the study proposes a different relationship between the variable and the probability that a firm will receive a bid. For example, although leverage has been used as a control variable in some takeover prediction research (e.g., Palepu (1986), Ambrose and Megginson (1992), Powell (1997), Espahbodi and Espahbodi (2003), Brar et al. (2009)), there has been no theoretical explanation of (or hypothesis on) the relationship between leverage and takeover likelihood. The reported findings on leverage have been inconsistent across studies (further discussed in 3.3.3). This issue is further discussed in section 3.3.

Section 5.2 shows that several of the old hypotheses are not empirically supported. This suggests that the old hypotheses, perhaps, do not really explain why certain firms receive takeover bids. This study contributes to the literature by introducing new variables/hypotheses to the takeover prediction literature and by developing and testing 'new' hypotheses based on theory using 'old' variables. Similar to section 5.2 above, the tests conducted in this section employ univariate analysis (descriptive statistics) and logit regression analysis. Piecewise regression analysis and centering of curvilinear variables are introduced to ascertain robustness in the analysis (these methods are discussed further in section 4.3.3). The new hypotheses tested in this section include: the firm size hypothesis, firm capital structure hypothesis, financial distress hypothesis, firm lifecycle hypothesis, M&A rumours hypothesis, payroll synergies hypothesis, share repurchase hypothesis, asymmetric valuation hypothesis, industry concentration hypothesis, market liquidity hypothesis and market economics hypothesis.

5.3.2 Firm size hypothesis (new)

The results from table 5.2.1 panel B (further discussed in section 5.2.9) confirms that contrary to the (old) firm size hypothesis, targets are, perhaps, not the smallest firms in the population. The average (or median) target is significantly (at the 1% level) larger than the average (or median) non-target. The results from the 25th percentile and 75th percentile also support this finding. Contrary to the old firm size hypothesis, the results from models 1A, 1B, 1C and 1D (table 5.2.1b) show that takeover probability increases with firm size. This is counterintuitive as it is unlikely that the biggest firms in the population are most at risk of becoming targets. The (new) firm size hypothesis put forward in this study, argues that firm size has an inverted U-shape relationship with takeover probability. This hypothesis of a nonlinear (inverted U-shaped) relationship between size and takeover likelihood is fully discussed in section 3.3.2. Table 5.3.2a presents results obtained from tests of this hypothesis.

Table 5.3.2a: The relationship between firm size and takeover probability

Panel A: Regression results with robust standard errors

Hypotheses	Proxies	Model 2A	Model 2B	Model 2C	Model 2D	Model 2E
Firm Size	Ln Assets (+)	1.136***	2.119***	2.155***	0.147***	0.153***
	Ln Assets Sq.(-)	-0.045***	-0.055***	-0.056***	-0.055***	-0.056***
Inefficient	Profitability (-)		-0.046	-0.047	-0.046	-0.047
Management	ADAR (-)		-83.844***	-82.517***	-83.844***	-82.517***
Undervaln	BTM(+)		-0.171***	-0.136**	-0.171***	-0.136**
Growth-	S. Growth (+/-)		-0.108	-0.111	-0.108	-0.111
resource	Liquidity (+/-)		-0.414	-0.377	-0.414	-0.377
Mismatch	Leverage(+/-)		0.059	0.056	0.059	0.056
	GRDummy (+)		-0.050	-0.055	-0.050	-0.055
Industry Dist.	IDUMMY (+)		0.007	-0.016	0.007	-0.016
Free Cash Flow	FCF (+)		0.545*	0.502*	0.545*	0.502*
Tangible assets	PPP/TA (+)		0.532**	0.482***	0.532***	0.482***
Firm Age	Age (-)		-0.003***	-0.003***	-0.003***	-0.003***
Constant		-26.209***	-22.822***	-23.303***	-23.303***	-2.702***
Industry dummies		NO	NO	YES	NO	YES
Firm size centred		NO	NO	NO	YES	YES
Observations		32,354	16,854	16,854	18,638	16,854
Deviance(–2LL)		12,819	7,174	7,164	9,555	7,164
Pseudo-R^2		0.008	0.010	0.011	0.010	0.011
LR Test of Coefficients		177.021***	169.762***	188.333***	188.250***	188.333***

Panel B: Regression results with clustered robust (Rogers) standard errors

Hypotheses	Proxies	Model 2F (Firm)	Model 2G (Year)	Model 2H (Industry)
Firm Size	Ln Assets (+)	2.119***	2.119***	2.119***
	Ln Assets Sq.(-)	-0.055***	-0.055***	-0.055***
Control variables (in model 2B)		YES	YES	YES
Constant		YES	YES	YES

Notes: The table presents the results of logit regression analysis where the dependent variable is takeover probability (bivariate), the independent variables are firm size (Ln total assets) and firm size squared (Ln total assets squared) and the control variables are the old prediction hypotheses. Profitability is the ratio of EBITDA to total capital employed. ADAR is the average daily abnormal return. Book to market (BTM) is the ratio of book value of equity to market value of equity. Sales growth is the rate of change in total revenues from the previous period. Liquidity is the ratio of cash and short term investments to total assets. Leverage is the firm's debt to equity ratio. GRDummy takes a value of 1 when there is a mismatch between a firm's growth opportunities and its resources and a value of 0 otherwise. IDummy takes a value of 1 if a takeover occurs in a firm's industry and a value of 0 otherwise. FCF/TA is the ratio of free cash flow (operating cash flow less capital investments) to total assets. PPE/TA is the ratio of tangible assets (property, plant and equipment) to total assets. Age is the number of years since incorporation. The hypothesised sign is shown in brackets (e.g., (+), (-)).Model 2A represents a logit regression model where the dependent variable is takeover probability and the independent variables are firm size (Ln total assets) and firm size squared (Ln total assets squared). This model has no control variables. Model 2B–2E are multivariate logit models with firm size as the independent variable and all the old variables as control variables, regressed on firm takeover probability. Model 2C is similar to 2B but also controls for industry using industry dummies. Model 2D replicates model 2B but centres the independent variable – firm size – (about the mean) to reduce the effect of multicollinearity in the model. Model 2E replicates model 2D but controls for industry differences using industry dummies (see table 4.2.2 for industry classifications). Models 2F, 2G and 2H are equivalent to model 2B adjusted for firm, year and industry clustering, respectively. 'Observations' is size of the sample used in the analysis, deviance is the -2Log likelihood ratio of the model and the test of model coefficient is the Chi Square test. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

The coefficients of firm size and firm size squared are positive and negative respectively (significant at the 1% level) across all five models (2A–2E). The results show that the relationship between firm size and takeover probability is nonlinear and follows an inverted U-shape function, as suggested by the new firm size hypothesis (discussed in section 3.3.2). This hypothesised inverted U-shaped relationship appears to be robust to different model specifications (see models 2C, 2D and 2E). For example, the relationship persists when firm size (the natural log of total assets) is centred about the mean or when industry dummies are included in the model. The inclusion of firm size squared to the old model substantially increases the pseudo R square by 42.85% from 0.007 (see table 5.2.1b) to 0.010 (see table 5.3.2a). The relationship remains robust when standard errors are corrected for clustering across firm, years and industries as in panel B. The contribution of the new variables to the old model is further discussed in section 6.2.

For additional robustness, piecewise regression analysis (discussed in section 4.3.3) is employed to confirm the findings obtained above. The sample of firms is divided into five quintiles which are generated by ranking all the firms in the sample by their firm size, then splitting them into five equal groups (groups 1 to 5). Group 1 represents the smallest 20% of firms in the sample and group 5 represents the largest 20% of firms in the sample. If the new firm size hypothesis holds, there is likely to be a positive relationship between takeover probability and firm size for firms in group 1 (small firms) and a negative relationship between takeover probability and firm size for firms in group 5 (large firms). The descriptive statistics for the different groups are presented in table 5.3.2b.

Table 5.3.2b: Descriptive statistics of firm size groups

	N	Range	Min.	Max.	Mean	Mean (£)	Std. Dev.	Skewness
Group 1	6,471	9.034	6.908	15.942	14.750	£2,546,456	1.155	-1.993
Group 2	6,471	1.101	15.942	17.043	16.524	£15,007,773	0.315	-0.129
Group 3	6,471	1.002	17.044	18.046	17.533	£41,140,491	0.288	0.074
Group 4	6,471	1.435	18.046	19.481	18.677	£129,185,635	0.406	0.229
Group 5	6,471	6.494	19.482	25.976	21.052	£1,388,709,110	1.192	0.909

Notes: The table shows descriptive statistics for different size quintiles. Groups (1-5) are generated by ranking all firms in the sample by their firm size and splitting the sample into five equal groups (quintiles). Group 1 contains the smallest 20% of firms in the sample and Group 5 contains the largest 20% of firms in the sample.

The average firm size (natural log of total assets) of firms in group 1 is 14.75 (equivalent to £2.55 million). The largest firm in that group has a firm size of £8.39 million. The distribution is slightly negatively skewed (and the range is broad) with some firms reporting low total asset values. The average firm in group 5 has total assets of £1.39 billion.

As shown in panels A and B (table 5.3.2c), I estimated two piecewise regression models, one without industry dummies and the other controlling for industry effects. The two models retain the old prediction variables as control variable. For simplicity, only the result for the key variable (firm size) is presented in table 5.3.2c. The results for the other variables are broadly similar to those presented in table 5.3.2a.

Table 5.3.2c: Piecewise regression analysis for firm size groups – with and without industry dummies

		Group 1	Group 2	Group 3	Group 4	Group 5
Panel A: Piecewise regressions						
Firm Size	Ln (Total Assets)	0.745***	0.237	0.394*	0.890	-0.188***
	Control Variables	YES	YES	YES	YES	YES
	Industry Dummies	NO	NO	NO	NO	NO
	Constant	YES	YES	YES	YES	YES
Panel B: Piecewise regressions (with industry dummies)						
Firm Size	Ln (Total Assets)	0.736***	0.229	0.455*	0.100	-0.190***
	Control Variables	YES	YES	YES	YES	YES
	Industry Dummies	YES	YES	YES	YES	YES
	Constant	YES	YES	YES	YES	YES

Notes: The table presents the results of logit regression analysis for different quintiles of firm size where the dependent variable is takeover probability (bivariate), the independent variable is firm size (Ln total assets) and the control variables in the model include profitability, ADAR, book to market ratio, sales growth, liquidity, leverage, GRDummy, IDummy, free cash flow ratio, tangible assets ratio, and firm age. Profitability is the ratio of EBITDA to total capital employed. ADAR is the average daily abnormal return. Book to market (BTM) is the ratio of book value of equity to market value of equity. Sales growth is the rate of change in total revenues from the previous period. Liquidity is the ratio of cash and short term investments to total assets. Leverage is the firm's debt to equity ratio. GRDummy takes a value of 1 when there is a mismatch between a firm's growth opportunities and its resources and a value of 0 otherwise. IDummy takes a value of 1 if a takeover occurs in a firm's industry and a value of 0 otherwise. FCF/TA is the ratio of free cash flow (operating cash flow less capital investments) to total assets. PPE/TA is the ratio of tangible assets (property, plant and equipment) to total assets. Age is the number of years since incorporation. Industry dummies include dummies for the industry groups shown in table 4.2.2. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

The results confirm that takeover probability increases in firm size for firms in group 1 (significant at the 1% level) and decreases in firm size for firms in group 5 (significant at the 1% level). These results reinforce the finding that takeover probability has an inverted U-shaped relationship with firm size, with the smallest and largest firms appearing to be more shielded from takeover activity, all else equal.

These results are important from a modelling perspective for researchers (or investors) employing the full sample of listed firms in their analysis. It is worth noting that several studies (see, for example Brar et al. (2009)) typically restrict their samples to larger firms. I find that the hypothesised relationship is still robust (significant at the 5% level) even when firms in group 1 (i.e., firms with total assets below £8.39 million) are excluded from the sample. The relationship only ceases to be significant when firms in groups 3 to 5 are considered (i.e., when 40% of the population of firms is left out of the analysis). The discrepancy between the results reported here and the results in the prior takeover prediction literature can be attributed to the manner in which the sample in this study is designed. This study uses a panel sample and employs the full sample of (UK) listed firms while several prior studies employ non-representative matched-samples, which are sometimes restricted to large listed firms (see, for example, Palepu et al. (1986), Espahbodi and Espahbodi (2003) Brar et al. (2009) and Ouzounis et al. (2010)).

5.3.3 Firm capital structure hypothesis

The firm capital structure hypothesis proposed in this study argues that takeover probability should increase with leverage up to the point where leverage becomes ‘too high’ for a potential bidder. At this point, takeover probability should start to decline with leverage. Overall, an inverted U-shape relationship should exist between leverage and takeover probability. The theoretical foundations of this hypothesis are discussed in section 3.3.3. In line with the hypothesis, the results show that there is a curvilinear relationship between takeover probability and firm leverage. As discussed in section 3.3.3, this hypothesised curvilinear relationship is tested by adding a squared leverage term in the model and testing for its significance as shown in table 5.3.3a.

There is no consensus on the relationship between capital structure and takeover likelihood in the literature. Palepu (1986) finds a significant negative relationship between takeover probability and leverage, Powell (1997) reports an insignificant negative relationship between takeover probability and leverage, Barnes (1998, 2000) finds a positive but insignificant relationship between takeover probability and leverage and Brar et al. (2009) argue that leverage has no explanatory power on takeover likelihood (and excludes the variable from their model). Other researchers (e.g., Powell and Yawson (2007)) have included leverage as a proxy for growth-resource imbalances without any indication of its potential effect on takeover probability.

Table 5.3.3a: The relationship between leverage and takeover probability
Panel A: Regression results with robust standard errors

Hypotheses	Proxies	3A	3B	3C	3D	3E
Firm capital	Leverage (+)	0.656***	0.345**	0.356**	0.222**	0.226**
structure	Leverage Sq. (–)	-0.212***	-0.116*	-0.123**	-0.116*	-0.123**
Inefficient	Profitability (-)		0.094	0.0812	0.094	0.081
Management	ADAR (-)		-82.636***	-81.579***	-82.636***	-81.579***
Underval.	BTM(+)		-0.131**	-0.099	-0.131	-0.099
GR	S. Growth (+/–)		-0.087	-0.086	-0.087	-0.086
Mismatch	GRDummy (+)		-0.080	-0.087	-0.080	-0.087
Industry Dist.	IDummy (+)		-0.008	-0.023	-0.008	-0.023
FreeCashFlow	FCF(+)		0.938***	0.907***	0.938***	0.907***
TangibleAssets	PPP/TA(+)		0.586***	0.536***	0.586***	0.535***
Firm Size	Ln TA (+)		0.034**	0.043**	0.034**	0.043**
Firm Age	Age (-)		-0.003***	-0.003***	-0.003***	-0.003***
Constant Term		-3.127***	-3.564***	-3.794***	-3.414***	-3.639***
Industry dummies		NO	NO	YES	NO	YES
Leverage centred		NO	NO	NO	YES	YES
Observations		32,348	16,856	16,856	16,856	16,856
Deviance(–2LL)		12,918	7,206	7,196	7,206	7,196
Pseudo-R^2		0.001	0.006	0.007	0.006	0.007
LR Test of Coefficients		42.842 ***	104.249 ***	123.963 ***	104.249 ***	123.963 ***

Panel B: Regression results with clustered robust standard errors

Hypotheses	Proxies	Model 3F (Firm)	Model 3G (Year)	Model 3H (Industry)
Firm capital	Leverage (+)	0.345**	0.345**	0.345***
structure	Leverage Sq. (–)	-0.116*	-0.116**	-0.116*
Control variables (in model 3B)		YES	YES	YES
Constant		YES	YES	YES

Notes: The table presents the results of logit regression analysis where the dependent variable is takeover probability (bivariate), the independent variables are firm leverage (total debt to total equity ratio) and firm leverage squared (total debt to total ratio squared) and the control variables are the old prediction hypotheses. Profitability is the ratio of EBITDA to total capital employed. ADAR is the average daily abnormal return. Book to market (BTM) is the ratio of book value of equity to market value of equity. Sales growth is the rate of change in total revenues from the previous period. Liquidity is the ratio of cash and short term investments to total assets. GRDummy takes a value of 1 when there is a mismatch between a firm's growth opportunities and its resources and a value of 0 otherwise. IDummy takes a value of 1 if a takeover occurs in a firm's industry and a value of 0 otherwise. FCF/TA is the ratio of free cash flow (operating cash flow less capital investments) to total assets. PPE/TA is the ratio of tangible assets (property, plant and equipment) to total assets. Firm size is the natural log of total assets. Age is the number of years since incorporation. The hypothesised sign is shown in brackets (e.g., (+), (-)). Model 3A represents a univariate logit regression model where the dependent variable is takeover probability and the independent variables are firm leverage and firm leverage squared. This model has no control variables. Model 3B – 3E are multivariate logit models with leverage as the independent variable and all the old variables as control variables, regressed on firm takeover probability. Model 3C is similar to 3B but also controls for industry using industry dummies. Model 3D replicates model 3B but centres the independent variable – leverage – (about the mean) to reduce the effect of multicollinearity in the model. Model 3E replicates model 3D but controls for industry differences using industry dummies (see table 4.2.2 for industry classifications). Models 3F, 3G and 3H are equivalent to model 3B adjusted for firm, year and industry clustering, respectively. 'Observations' is size of the sample used in the analysis, deviance is the -2 log likelihood ratio of the model and the test of model coefficient is the Chi Square test. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

As shown in table 5.3.3a, the coefficients of leverage and leverage squared are positive and negative respectively (significant at the 5% level) across models 3A to E. The results are robust to mean-centering as well as controlling for industry differences. The relationship remains robust when standard errors are corrected for clustering across firm, years and industries as in panel B. The results show that the relationship between leverage and takeover probability is curvilinear and follows an inverted U-shape function, as suggested by the hypothesis (discussed in section 3.3.3). Consistent with the hypothesis, the findings suggest that the effect of capital structure on takeover probability can, perhaps, be captured by modelling the relationship under a nonlinear framework.

Piecewise regression analysis (similar to the analysis discussed in section 5.3.2) is used as a robustness check and to understand this relationship further. The firms in the sample are ranked by leverage and grouped into five quintiles. The descriptive statistics for the different quintiles are presented in table 5.3.3b (see panel A). About 20% of the observations in the sample report zero leverage.

Table 5.3.3b: Descriptive statistics of leverage groups

	N	Range	Minimum	Maximum	Mean	Std. Dev	Skewness
Group 1	6,470	0.001	0.000	0.001	0.000	0.000	5.550
Group 2	6,469	0.150	0.001	0.151	0.059	0.045	0.431
Group 3	6,471	0.247	0.151	0.398	0.269	0.072	0.090
Group 4	6,468	0.393	0.398	0.791	0.568	0.111	0.280
Group 5	6,470	1.898	0.791	2.689	1.574	0.690	0.619

Notes: The table shows descriptive statistics for different leverage quintiles. Groups are generated by ranking all firms in the sample by their leverage and splitting the sample into five equal groups (quintiles). Group 1 contains the 20% of firms with the lowest leverage in the sample and Group 5 contains the 20% of firms with the highest leverage in the sample. Group 1 is made up of firms which do not employ substantial long term debt in their capital structure.

The results in table 5.3.3b shows that several firms in the sample employ very little debt (see group 1). The average firm in group 5 is heavily levered – debt of 157% of its equity. The relationship between leverage and takeover probability for firms in group 1–5 is reported in table 5.3.3c.

Table 5.3.3c: Piecewise regression analysis for leverage groups – with and without industry dummies

		Group 1	Group 2	Group 3	Group 4	Group 5
Panel A: Piecewise regressions – equal samples						
Firm Capital Structure	Leverage	135.485	-2.738	-1.019	1.281**	0.075
	Control Variables	YES	YES	YES	YES	YES
	Industry Dummies	NO	NO	NO	NO	NO
	Constant	YES	YES	YES	YES	YES
Panel B: Piecewise regressions with industry dummies – equal samples						
Firm Capital Structure	Leverage	139.858	-2.317	-0.932	1.251**	0.056
	Control Variables	YES	YES	YES	YES	YES
	Industry Dummies	YES	YES	YES	YES	YES
	Constant	YES	YES	YES	YES	YES

Notes: The table presents the results of logit regression analysis for different quintiles of leverage where the dependent variable is takeover probability (bivariate), the independent variable is firm leverage (total debt to total equity) and the control variables in the model include profitability, ADAR, book to market ratio, sales growth, liquidity, leverage, GRDummy, IDummy, free cash flow ratio, tangible assets ratio, firm size and firm age. Profitability is the ratio of EBITDA to total capital employed. ADAR is the average daily abnormal return. Book to market (BTM) is the ratio of book value of equity to market value of equity. Sales growth is the rate of change in total revenues from the previous period. Liquidity is the ratio of cash and short term investments to total assets. Leverage is the firm's debt to equity ratio. GRDummy takes a value of 1 when there is a mismatch between a firm's growth opportunities and its resources and a value of 0 otherwise. FCF/TA is the ratio of free cash flow (operating cash flow less capital investments) to total assets. PPE/TA is the ratio of tangible assets (property, plant and equipment) to total assets. Firm size is the natural log of the firm's total assets. Age is the number of years since incorporation. Industry dummies include dummies for the industry groups shown in table 4.2.2. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

The results show that takeover probability has a significantly positive relationship with leverage for firms in group 4. This positive relationship is not consistent for higher levels of leverage – group 5 (as suggested by the hypothesis). The finding is robust to industry variations. The piecewise regression analysis provides some support for the argument that the relationship between takeover likelihood and leverage is non-linear.

5.3.4 Financial distress hypothesis

The financial distress hypothesis (as discussed in section 3.3.4) argues that takeover likelihood, potentially, increases with the degree of financial distress (measured using Taffler's Z scores). The hypothesis further argues that firms with a high probability of going bankrupt (i.e., firms with Z scores below 0) will have a low takeover probability due to the added risk to be borne by a potential bidder. The first (second) part of the hypothesis is tested by examining the relationship between takeover probability and firm Z scores (Z score dummies). This hypothesis is fully discussed in section 3.3.4.

The results in table 5.2.1 show that targets have lower Z scores than non-targets, on average. That is, targets have an average Z score of 25.954 while non-targets have an average Z score of 29.954. The difference in mean Z score between the two groups is statistically significant at the 10% level. The U-test confirms that the distributions of the Z score variable for targets and non-targets are significantly different (at the 5% level). The median test also provides further statistical support for the hypothesis as targets have a median Z score value of 7.434 which is significantly different (at the 1% level) from the 8.212 median Z score of non-targets.

The results from the regression analysis are presented in table 5.3.4. The multivariate results in table 5.3.4 do not support the hypothesis that takeover likelihood decreases with Z score. The results show that, consistent with the hypothesis, takeover probability is negatively related to firm's Z scores but this relationship is not statistically significant. The second part of the hypothesis suggested that highly distressed firms will have a lower takeover likelihood, compared to their non-distress counterparts, all else equal. The ZSDummy is used to test this hypothesis (further discussed in section 3.3.4).

The ZSDummy takes a value of 1 when the Z score is negative (below 0) and a value of 0 otherwise. Of the 32,363 firm-years in the sample, 5,242 firm-years are associated with negative Z scores (i.e., ZSDummy = 1) of which 5.00% or 260 firm-years receive takeover bids. Therefore, 15.90% of the 1,635 takeover targets in the sample have negative Z scores prior to receiving takeover bids. This indicates that a majority (85.1%) of targets can be considered as 'non-distressed' firms. This relationship is further tested under a multivariate framework as shown in table 5.3.4.

Table 5.3.4: The relationship between level of financial distress and takeover probability

Panel A: Regression results with robust standard errors

Hypotheses	Proxies	Model 4A	Model 4B	Model 4C
Financial distress	Z Score (-)	-0.001***	-0.000	-0.000
	ZSDummy (-)	-0.151**	-0.239**	-0.238**
Inefficient	Profitability (-)		0.017	0.025
Management	ADAR (-)		-91.152***	-89.880***
Underval.	BTM(+)		-0.129*	-0.090
GR	S. Growth (+/–)		-0.049	-0.053
Mismatch	Liquidity (+/–)		-0.722**	-0.631*
	Leverage (+/–)		0.089	0.086
	GRDummy (+)		-0.068	-0.072
Industry Dist.	IDummy (+)		0.028	0.008
Free Cash Flow	FCF(+)		0.725**	0.688**
Tangible assets	PPP/TA(+)		0.539***	0.489***
Firm Size	Ln TA (+)		0.034*	0.043**
Firm Age	Age (-)		-0.003***	-0.003**
Constant Term		-2.812***	-3.367***	-3.630***
Industry dummies		NO	NO	YES
Observations		27,336	14,684	14,684
Deviance(–2LL)		11,384	6,405	6,396
Pseudo-R^2		0.000	0.007	0.008
LR Test of Coefficients		9.596***	98.264***	115.826***

Panel B: Regression results with clustered robust standard errors

Hypotheses	Proxies	Model 4D (Firm)	Model 4E (Year)	Model 4F (Industry)
Financial distress	Z Score (-)	-0.000	-0.000	-0.000
	ZSDummy (-)	-0.239**	-0.239***	-0.239**
Control variables (in model 4B)		YES	YES	YES
Constant		YES	YES	YES

Notes: The table presents the results of logit regression analysis where the dependent variable is takeover probability (bivariate), the independent variables are proxies of the financial distress hypothesis (Z Score and ZSDummy) and the control variables are the old prediction hypotheses. ZScore refers to a firm's Taffler Z score. ZSDummy takes a value of 1 if a firm's Z Score is negative and a value of 0 otherwise. Profitability is the ratio of EBITDA to total capital employed. ADAR is the average daily abnormal return. Book to market (BTM) is the ratio of book value of equity to market value of equity. Sales growth is the rate of change in total revenues from the previous period. Liquidity is the ratio of cash and short term investments to total assets. Leverage is the ratio of total debt to total equity. GRDummy takes a value of 1 when there is a mismatch between a firm's growth opportunities and its resources and a value of 0 otherwise. IDummy takes a value of 1 if a takeover occurs in a firm's industry and a value of 0 otherwise. FCF/TA is the ratio of free cash flow (operating cash flow less capital investments) to total assets. PPE/TA is the ratio of tangible assets (property, plant and equipment) to total assets. Firm size is the natural log of total assets. Age is the number of years since incorporation. The hypothesised sign is shown in brackets (e.g., (+), (-)).Model 4A represents a univariate logit regression model where the dependent variable is takeover probability and the independent variables are Z score and ZSDummy. This model has no control variables. Model 4B and 4C are multivariate logit models with Z score and ZSDummy as the independent variables and all the old variables as control variables, regressed on firm takeover probability. Model 4C is similar to 4B but also controls for industry using industry dummies (see table 4.2.2 for industry classifications). Models 4F, 4G and 4H are equivalent to model 4B adjusted for firm, year and industry clustering, respectively. 'Observations' is size of the sample used in the analysis, deviance is the -2 log likelihood ratio of the model and the test of model coefficient is the Chi Square test. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

The expectation is that the coefficient of the ZSDummy should be negative indicating that firms with negative Z scores have a lower likelihood of receiving a bid. The results shown in table 5.3.4 (models 4A–4C) indicate that raw Taffler Z scores have no predictive power in the sample. ZSDummy has a negative coefficient in model 3A to 3C (significant at the 5% level). The negative sign of the coefficient indicates that, consistent with the hypothesis, as Z scores fall below 0 (ZSDummy takes a value of 1) the probability that the firm will receive a bid reduces. The relationship remains robust when standard errors are corrected for clustering across firm, years and industries as in panel B. The indication is that firms in financial distress are less likely to become takeover targets. The results broadly contradict the findings of Powell and Yawson (2007), who argue bankrupt (highly distressed) firms are similar to takeover targets. The results indicate that while financial distress potentially increases the likelihood of takeover, highly distressed firms (with Z score below 0) are unlikely to be attractive takeover targets.

5.3.5 Firm lifecycle hypothesis

The firm survival literature has established that young firms face a higher risk of industry exit compared to older firms. The empirical results discussed in section 5.2.9 (on firm age hypothesis) support this contention. This finding, however, leaves much to be answered about what eventually happens to firms as they grow old[157]. In line with Loderer and Waelchli (2010), the firm age hypothesis is expanded into the firm lifecycle hypothesis which attempts to develop a more holistic view of how takeover probability varies with firm age. The hypothesis (discussed in section 3.3.5) suggests that firm age is a U-shaped function of takeover probability. Here, takeover probability is hypothesised to initially decline with age and subsequently increases with age as firms grow old. The results of tests of this hypothesis are presented in table 5.3.5a.

[157] It is unlikely that firms live perpetually (Loderer and Waelchli (2010)) but there is no empirical relationship between bankruptcy and firm age (Shumway (2001)).

Table 5.3.5a: The relationship between firm age and takeover probability
Panel A: Regression results with robust standard errors

Hypotheses	Proxies	5A	5B	5C	5D	5E
Firm Life cycle	Age (-)	-0.004	-0.004	-0.004	-0.004**	-0.004*
	Age sq. (+)	0.000	0.000	0.000	0.000	0.000
Inefficient	Profitability (-)		0.062	0.056	0.062	0.056
Management	ADAR (-)		-83.270***	-82.187***	-83.270***	-82.187***
Undervaluatn.	BTM(+)		-0.119*	-0.086	-0.119*	-0.086
Growth	S. Growth (+/–)		-0.076	-0.076	-0.076	-0.076
Resource	Liquidity (+/–)		-0.609**	-0.557*	-0.609**	-0.557*
Mismatch	Leverage (+/–)		0.043	0.040	0.043	0.040
	GRDummy(+)		-0.030	-0.040	-0.030	-0.040
Industry Dist.	IDUMMY(+)		-0.009	-0.024	-0.009	-0.024
Free Cash Flow	FCF(+)		0.913***	0.881***	0.913***	0.881***
Tangible assets	PPP/TA(+)		0.517**	0.480***	0.517***	0.480***
Firm Size	Ln Assets (-)		0.040**	0.049***	0.040**	0.049***
Constant Term		-2.653***	-2.975***	-3.734***	-3.615***	-3.852***
Industry dummies		NO	NO	YES	NO	YES
Age centred		NO	NO	NO	YES	YES
Observations		26,588	16,854	16,854	18,373	16,830
Deviance(–2LL)		12,206	7,205	7,196	7,196	7,196
Pseudo-R^2		0.001	0.006	0.007	0.006	0.007
LR Test of Coefficients		26.135***	105.609***	124.027***	105.609***	124.027***

Panel B: Regression results with clustered robust standard errors

Hypotheses	Proxies	Model 5F (Firm)	Model 5G (Year)	Model 5H (Industry)
Firm Life cycle	Age (-)	-0.004	-0.004	-0.004
	Age sq. (+)	0.000	0.000	0.000
Control variables (in model 5B)		YES	YES	YES
Constant		YES	YES	YES

Notes: The table presents the results of logit regression analysis where the dependent variable is takeover probability (bivariate), the independent variables are firm age and firm age squared and the control variables are the old prediction hypotheses. The coefficients of firm age squared are small and positive but are shown as 0.000 (3 decimal places) due to space limitations. Profitability is the ratio of EBITDA to total capital employed. ADAR is the average daily abnormal return. Book to market (BTM) is the ratio of book value of equity to market value of equity. Sales growth is the rate of change in total revenues from the previous period. Liquidity is the ratio of cash and short term investments to total assets. Leverage is the ratio of total debt to total equity. GRDummy takes a value of 1 when there is a mismatch between a firm's growth opportunities and its resources and a value of 0 otherwise. IDummy takes a value of 1 if a takeover occurs in a firm's industry and a value of 0 otherwise. FCF/TA is the ratio of free cash flow (operating cash flow less capital investments) to total assets. PPE/TA is the ratio of tangible assets (property, plant and equipment) to total assets. Firm size is the natural log of total assets. Age is the number of years since incorporation. The hypothesised sign is shown in brackets (e.g., (+), (-)). Model 5A represents a univariate logit regression model where the dependent variable is takeover probability and the independent variables are firm age and firm age squared. This model has no control variables. Model 5B and 5C are multivariate logit models with firm age and firm age squared as the independent variables and all the old variables as control variables, regressed on firm takeover probability. Model 5C is similar to 5B but also controls for industry using industry dummies (see table 4.2.2 for industry classifications). Model 5D and 5E used centre values (about the mean) for firm age and firm age squared. Models 5F, 5G and 5H are equivalent to model 5B adjusted for firm, year and industry clustering, respectively. 'Observations' is size of the sample used in the analysis, deviance is the -2 log likelihood ratio of the model and the test of model coefficient is the Chi Square test. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

The argument that old firms do not typically ‘die’ but are recycled into new firms through acquisitions (proposed by Loderer and Waelchli (2010)) is not empirically supported. The results in table 5.3.5 (model 5A to 5E), shows that the coefficient of the Age squared variable is positive (but not statistically significant). The results do not therefore support the firm lifecycle hypothesis proposed in this study. The question of what happens to firms as they grow old is therefore still very much open for debate.

As in section 5.3.2 and section 5.3.3, further analysis on the relationship between the distribution of firm age and takeover probability can be conducted by using different age subgroups. The sample of firms is ranked by age and (group 1- group 5) quintiles are created. The descriptive statistics of the five groups are shown in table 5.3.5b.

Table 5.3.5b: Descriptive statistics of firm age groups

	N	Range	Minimum	Maximum	Mean	SD Dev.	Skewness
Group 1	6,614	5	0	5	2.704	1.592	-0.094
Group 2	5,463	5	6	11	8.288	1.679	0.154
Group 3	6,018	14	12	26	17.784	4.265	0.336
Group 4	5,864	37	27	64	44.294	11.133	0.091
Group 5	5,927	99	65	164	87.891	15.772	0.677

Notes: The table shows descriptive statistics for different firm age quintiles. Groups are generated by ranking all firms in the sample by their firm age and splitting the sample into five equal groups (quintiles). Group 1 contains the youngest 20% of firms in the sample and Group 5 contains the oldest 20% of firms in the sample.

Group 1 consists of young firms (with incorporation age of under five years). The average age of firms in this group is 2.7 years. The average age of firms increase from one group to the other, with firms in group five having an average age of 87.9 years. The oldest firm is 164.0 years old. The skewness of within-group distributions is low. The results of the regression analysis between firm age and takeover probability for different firm age groups (controlling for other determinants of takeover probability) are shown in table 5.3.5c. For conciseness, the regression coefficients for the control variables are not presented as they are in line with the results shown in table 5.3.5a.

Table 5.3.5c: Piecewise regression analysis for firm age groups: with and without industry dummies

	Group 1	Group 2	Group 3	Group 4	Group 5	Group 1,2	Group 3,4,5
Panel A: Piecewise regressions							
Firm age	0.007	-0.020	-0.017	-0.006	-0.006	0.031*	-0.003**
Control Variables	YES	YES	YES	YES	YES	YES	YES
Industry Dummies	NO	NO	NO	NO	NO	NO	NO
Constant	YES	YES	YES	YES	YES	YES	YES
Panel B: Piecewise regressions (with industry dummies)							
Firm age	0.012	-0.021	-0.018	-0.006	-0.006	0.032*	-0.003**
Control Variables	YES	YES	YES	YES	YES	YES	YES
Industry Dummies	YES	YES	YES	YES	YES	YES	YES
Constant	YES	YES	YES	YES	YES	YES	YES

Notes: The table presents the results of logit regression analysis for different quintiles of firm age where the dependent variable is takeover probability (bivariate), the independent variable is firm age (number of years since incorporation) and the control variables in the model include profitability, ADAR, book to market ratio, sales growth, liquidity, leverage, GRDummy, IDummy, free cash flow ratio, tangible assets ratio, firm size and firm age. Profitability is the ratio of EBITDA to total capital employed. ADAR is the average daily abnormal return. Book to market (BTM) is the ratio of book value of equity to market value of equity. Sales growth is the rate of change in total revenues from the previous period. Liquidity is the ratio of cash and short term investments to total assets. Leverage is the firm's debt to equity ratio. GRDummy takes a value of 1 when there is a mismatch between a firm's growth opportunities and its resources and a value of 0 otherwise. FCF/TA is the ratio of free cash flow (operating cash flow less capital investments) to total assets. PPE/TA is the ratio of tangible assets (property, plant and equipment) to total assets. Firm size is the natural log of the firm's total assets. Industry dummies include dummies for the industry groups shown in table 4.2.2. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

The coefficient of firm age is statistically insignificant across all groups. Nonetheless, the results indicate that takeover probability is, perhaps, increasing in firm age below 11 years (groups 1 and 2) and decreasing in firm age between 11 and 164 years (groups 3, 4 and 5). The indication is that the negative relationship between firm age and takeover probability (discussed in sections 3.2.9 and 5.2.9) is mainly driven by older firms (i.e., firms with incorporation age between 11 and 164 years). This finding is robust to different model specifications as shown in table 5.3.5c. These findings broadly support prior empirical evidence suggesting that the probability of firm exit (through bankruptcies or takeovers) is negatively related to age due to a firm's ability to learn, actively or passively, over time (Hopenhayn (1992), Pakes and Ericson (1998) and Bhattacharjee et al. (2009)). The results are inconsistent with Loderer and Waelchli (2010) who argue that takeover hazard initially declines with age and then increases as firms grow older. The firm lifecycle hypothesis is therefore not empirically supported.

5.3.6 M&A rumours hypothesis

The M&A rumours hypothesis argues that the presence of merger rumours about a specific firm increases its takeover likelihood or indicates an increased takeover likelihood[158]. This hypothesis is fully discussed in section 3.3.6. Of the 32,363 firm-years in the sample, 0.53% or 173 firm-years are associated with merger rumours. 8.67% or 15 of these rumours are associated with subsequent takeover bids occurring within a one year period. The relationship between the presence of takeover rumours and takeover likelihood is analysed using a multivariate framework as shown in table 5.3.6.

In line with the hypothesis, there is a direct relationship between the presence of merger rumours and the associated firm's takeover probability. The relationship is significant (at the 5% level) in model 6A (with no control variables) but insignificant (in models 6B and 6C) when other drivers of takeover likelihood are controlled for. The results in model 6B are replicated in models 6D, 6E and 6F in which robust standard errors are also corrected for firm, year and industry clustering, respectively. The results broadly support the hypothesis that rumours increase the likelihood of takeovers (or indicate an increased takeover likelihood). As shown in table 4.3.2a, the M&A rumour dummy is not correlated with any other independent variable. This indicates the M&A rumours are informative and do not, necessarily, proxy for other determinants of takeovers. The findings in table 5.3.6 (while not statistically robust), perhaps, provide some support to Bommel (2003) – rumours are informative at equilibrium – and Pound (1990) and Jindra and Walking (2004) – several tender offers are preceded by rumours. The results, however, indicate that rumours have no significant residual value when included as part of the prediction model.

[158] No assumption is made about a cause-and-effect relationship between rumours and takeover likelihood.

Table 5.3.6: The relationship between merger rumours and takeover probability

Panel A: Regression results with robust standard errors

Hypotheses	Proxies	6A	6B	6C
Merger rumours	MRDummy (+)	0.583**	0.043	0.011
Inefficient	Profit (-)		0.060	0.054
Management	ADAR (-)		-83.311***	-82.229***
Underval.	BTM(+)		-0.120*	-0.088
GR	S. Growth (+/–)		-0.074	-0.073
Mismatch	Liquidity (+/–)		-0.605**	-0.554*
	Leverage (+/–)		0.042	0.040
	GRDummy (+)		-0.030	-0.040
Industry Dist.	IDummy (+)		-0.008	0.024
Free Cash Flow	FCF(+)		0.908***	0.875***
Tangible assets	PPP/TA(+)		0.520***	0.481***
Firm Size	Ln TA (+)		0.040**	0.048***
Firm Age	Age (-)		-0.003***	-0.003**
Constant Term		-2.890***	-2.863***	-3.746***
Industry dummies		NO	NO	YES
Observations		32,363	16,854	16,854
Deviance(–2LL)		12,946	7,205	7,196
Pseudo-R^2		0.000	0.006	0.007
LR Test of Coefficients		3.951**	105.564***	123.965***

Panel B: Regression results with clustered robust standard errors

Hypotheses	Proxies	Model 6D (Firm)	Model 6E (Year)	Model 6F (Industry)
Merger rumours	MRDummy (+)	0.043	0.043	0.043
Control variables (in model 6B)		YES	YES	YES
Constant		YES	YES	YES

Notes: The table presents the results of logit regression analysis where the dependent variable is takeover probability (bivariate), the independent variable is M&A rumours (MRDummy) and the control variables are the old prediction hypotheses. Profitability is the ratio of EBITDA to total capital employed. ADAR is the average daily abnormal return. Book to market (BTM) is the ratio of book value of equity to market value of equity. Sales growth is the rate of change in total revenues from the previous period. Liquidity is the ratio of cash and short term investments to total assets. Leverage is the ratio of total debt to total equity. GRDummy takes a value of 1 when there is a mismatch between a firm's growth opportunities and its resources and a value of 0 otherwise. IDummy takes a value of 1 if a takeover occurs in a firm's industry and a value of 0 otherwise. FCF/TA is the ratio of free cash flow (operating cash flow less capital investments) to total assets. PPE/TA is the ratio of tangible assets (property, plant and equipment) to total assets. Firm size is the natural log of total assets. Age is the number of years since incorporation. The hypothesised sign is shown in brackets (e.g., (+), (-)).Model 6A represents a univariate logit regression model where the dependent variable is takeover probability and the independent variable is the MRDummy. This model has no control variables. Model 6B is a multivariate logit model with MRDummy as the independent variable and all the old variables as control variables, regressed on firm takeover probability. Model 6C replicates model 6B but controls for industry differences using industry dummies (see table 4.2.2 for industry classifications). Models 6D, 6E and 6F are equivalent to model 6B adjusted for firm, year and industry clustering, respectively. 'Observations' is size of the sample used in the analysis, deviance is the -2 log likelihood ratio of the model and the test of model coefficient is the Chi Square test. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

The lack of robustness can partly be attributed to the significant weaknesses in the way the data for merger rumours is collected. The primary weakness, as noted in the hypotheses chapter, is the reliance on rumours available on Thomson DataStream. Over the study period, Thomson DataStream reports fewer than 500 merger rumour occurrences which can only be matched to 198 (of 32,363) distinct firm-years. A more holistic database (such as the Financial Times archives [FT CD Rom]) might, perhaps, provide a more complete dataset of merger rumours. However, such a dataset requires an item-level treatment approach which was considered infeasible for the current study given the sample size. These 'preliminary' results, nonetheless, pave the way for further studies in the area.

5.3.7 Payroll synergies hypothesis

The payroll synergy hypothesis contends that takeover probability is an inverse U-shaped function of a firm's payroll burden (HR cost to sales ratio)[159]. That is, takeover likelihood increases with payroll burden but declines when payroll burden becomes very high. This hypothesis is fully discussed in section 3.3.7. The descriptive statistics (table 5.2.1 panel B) indicate that, on average, targets have a lower payroll burden when compared to non-targets. On average non-targets pay 34.10% of their sales revenues to their employees as salaries and benefits, while targets pay 31.40%. The difference between the two subsamples is statistically significant at a 1% level. The result from the U-test is statistically insignificant. The median payroll bill is 25.70% of sales revenue for targets and 26.50% for non-targets. The difference in median is insignificant at the 10% level.

The payroll synergies hypothesis (U-shaped relationship) is further investigated using a multivariate framework as shown in table 5.3.7a. This is achieved by regressing HR costs to sales and squared HR Costs to sales on takeover probability (controlling for other determinants of takeover probability).

[159] HR (human resource) costs include expenses on employee salaries and benefits.

Table 5.3.7a: The relationship between HR costs (to sales) and takeover probability
Panel A: Regression results with robust standard errors

Hypotheses	Proxies	7A	7B	7C	7D	7E
Payroll	HR/Sales (+)	0.967***	1.063**	1.198**	0.420*	0.490*
Synergies	HR/Sales sq.(–)	-1.266***	-0.975**	-1.073**	-0.975**	-1.073**
Inefficient	Profitability (-)		-0.129	-0.134	-0.129	-0.134
Management	ADAR (-)		-76.714***	-75.316***	-76.714***	-75.316***
Underval	BTM(+)		-0.131*	-0.096	-0.131*	-0.096
Growth-	S.Growth (+/–)		-0.046	-0.041	-0.046	-0.041
resource	Liquidity (+/–)		-0.630**	-0.555*	-0.630**	-0.555*
Mismatch	Leverage (+/–)		-0.009	-0.006	-0.009	-0.006
	GRDummy(+)		0.003	-0.012	0.003	-0.012
Industry Dist.	IDummy(+)		0.011	-0.008	0.011	-0.008
FreeCash	FCF(+)		1.077***	1.047***	1.077***	1.047***
Tangible Asts	PPP/TA(+)		0.499***	0.445**	0.499***	0.445**
Firm Size	LnAssets (+)		0.068***	0.079***	0.068***	0.079***
Firm Age	Age (-)		-0.003**	-0.003***	-0.003**	-0.003***
Constant		-2.914***	-4.224***	-4.547***	-3.979***	-3.074**
Industry dummies		NO	NO	YES	NO	YES
HR Cost/Sales centred		NO	NO	NO	YES	YES
Observations		23,572	16,163	16,163	16,163	16,163
Deviance(–2LL)		10,260	6,678	6,668	6,678	6,668
Pseudo-R^2		0.001	0.006	0.008	0.006	0.008
LR Test of Coefficients		28.647***	102.829***	123.309***	102.828***	123.309***

Panel B: Regression results with clustered robust standard errors

Hypotheses	Proxies	Model 7F (Firm)	Model 7G (Year)	Model 7H (Industry)
Payroll	HR/Sales (+)	1.063**	1.063**	1.063**
Synergies	HR/Sales sq.(–)	-0.975**	-0.975**	-0.975**
Control variables (in model 7B)		YES	YES	YES
Constant		YES	YES	YES

Notes: The table presents the results of logit regression analysis where the dependent variable is takeover probability (bivariate), the independent variables are payroll costs to sales ratio and payroll costs to sales ratio squared and the control variables are the old prediction hypotheses. Profitability is the ratio of EBITDA to total capital employed. ADAR is the average daily abnormal return. Book to market (BTM) is the ratio of book value of equity to market value of equity. Sales growth is the rate of change in total revenues from the previous period. Liquidity is the ratio of cash and short term investments to total assets. Leverage is the ratio of total debt to total equity. GRDummy takes a value of 1 when there is a mismatch between a firm's growth opportunities and its resources and a value of 0 otherwise. IDummy takes a value of 1 if a takeover occurs in a firm's industry and a value of 0 otherwise. FCF/TA is the ratio of free cash flow (operating cash flow less capital investments) to total assets. PPE/TA is the ratio of tangible assets (property, plant and equipment) to total assets. Firm size is the natural log of total assets. Age is the number of years since incorporation. The hypothesised sign is shown in brackets (e.g., (+), (-)). Model 7A represents a univariate logit regression model where the dependent variable is takeover probability and the independent variables are HR cost to sales and squared HR cost to sales, with no control variables. Model 7B – 7E are multivariate logit models with HR cost to sales as the independent variable and all the old variables as control variables, regressed on firm takeover probability. Model 7C is similar to 7B but also controls for industry using industry dummies (see table 4.2.2 for industry classifications). Model 7D replicates model 7B but centres the independent variable – HR cost to sales – (about the mean) to minimise multicollinearity in the model. Model 7E replicates model 7D but controls for industry differences using industry dummies. Models 7F, 7G and 7H are equivalent to model 7B adjusted for firm, year and industry clustering, respectively. 'Observations' is size of the sample used in the analysis, deviance is the -2 log likelihood ratio of the model and the test of model coefficient is the Chi Square test. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

The coefficient of the HR cost to sales ratio is negative and statistically significant at the 10% level and the coefficient of the HR Cost to sales ratio squared is positive and statistically significant at the 10% level across all (five) model specifications[160]. The relationship remains robust when standard errors are corrected for clustering across firm, years and industries as in panel B. The distribution of firm payroll (HR) costs to sales ratio can be expected to substantially vary across industries as some industries are more labour intensive than others. Nonetheless, the results show that even after explicitly controlling for industry differences (as in model 7E) or correcting standard errors for clustering by industry (as in model 7H), the relationship between HR cost to sales ratio and takeover probability remains robust.

These results support the contention that takeover probability has a nonlinear relationship with payroll burden. As hypothesised, the results show that takeover probability, perhaps, initially decreases with payroll burden, then increases as payroll burden increases. Piecewise regression analysis is used to ensure robustness in the results. This is achieved by creating five quintiles (group 1- group 5) based on HR costs to sales ratio ranks. Firms in group 1 (group 5) are the 20% of firms in the sample with the lowest (highest) HR cost to sales ratio or payroll burden. If the hypothesised relationship is true, one will expect the relationship between payroll burden and takeover probability to, perhaps, be negative (and significant) for firms in group 1, and positive (and significant) for firms in group 5. It is likely that this relationship will be weak for firms in groups 3 as they, presumably, have the 'average' payroll burden or represent the turning point in the relationship. Table 5.3.7b shows the descriptive statistics of each of the five groups.

Table 5.3.7b: Descriptive statistics of HR costs to sales groups

	N	Range	Minimum	Maximum	Mean	SD Deviation	Skewness
Group 1	4,715	0.086	0.057	0.144	0.097	0.028	-0.064
Group 2	4,714	0.080	0.144	0.224	0.184	0.023	-0.015
Group 3	4,714	0.086	0.224	0.314	0.266	0.025	0.079
Group 4	4,714	0.147	0.310	0.457	0.370	0.042	0.376
Group 5	4,714	0.709	0.457	1.166	0.779	0.273	0.445

Notes: The table shows descriptive statistics for different HR cost to sales quintiles. Groups are generated by ranking all firms in the sample by their HR cost to sales ratio (payroll burden) and splitting the sample into five equal groups (quintiles). Group 1 contains the 20% of firms with the lowest payroll burden and Group 5 contains the 20% of firms with the highest payroll burden.

[160] Model 7D and 7E, which use centred variables, requires the coefficient of the squared term to be significant, to indicate nonlinearity.

Firms in group 1 have a mean HR cost to sales ratio of 9.7%. The distribution of HR cost to sales for group 1 is not (significantly) skewed. Firms in group 5 have an average HR cost to sales ratio of 77.9%. The results for the piecewise regression analysis are presented in table 5.3.7c.

Table 5.3.7c: Piecewise regression analysis for HR costs to sales groups – with and without industry dummies

		Group 1	Group 2	Group 3	Group 4	Group 5
Panel A: Piecewise regressions						
Payroll Synergies	HR cost/sales	1.638	4.980	-4.771	-2.032	-0.430
	Control Variables	YES	YES	YES	YES	YES
	Industry Dummies	NO	NO	NO	NO	NO
	Constant	YES	YES	YES	YES	YES
Panel B: Piecewise regressions (with industry dummies)						
Payroll Synergies	HR cost/sales	1.481	5.532*	-5.117*	-1.783	-0.358
	Control Variables	YES	YES	YES	YES	YES
	Industry Dummies	YES	YES	YES	YES	YES
	Constant	YES	YES	YES	YES	YES

Notes: The table presents the results of logit regression analysis for different quintiles of HR costs to sales where the dependent variable is takeover probability (bivariate), the independent variable is the HR (payroll) cost to sales ratio and the control variables in the model include profitability, ADAR, book to market ratio, sales growth, liquidity, leverage, GRDummy, IDummy, free cash flow ratio, tangible assets ratio, firm size and firm age. Profitability is the ratio of EBITDA to total capital employed. ADAR is the average daily abnormal return. Book to market (BTM) is the ratio of book value of equity to market value of equity. Sales growth is the rate of change in total revenues from the previous period. Liquidity is the ratio of cash and short term investments to total assets. Leverage is the firm's debt to equity ratio. GRDummy takes a value of 1 when there is a mismatch between a firm's growth opportunities and its resources and a value of 0 otherwise. FCF/TA is the ratio of free cash flow (operating cash flow less capital investments) to total assets. PPE/TA is the ratio of tangible assets (property, plant and equipment) to total assets. Firm size is the natural log of the firm's total assets. Age is the number of years since incorporation. Industry dummies include dummies for the industry groups shown in table 4.2.2. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

The relationship between takeover probability and payroll burden is positive for firms in groups 1 and 2 and negative for firms in groups 3, 4 and 5. The results are statistically significant when industry differences are controlled for. These results support the hypothesis that takeover probability increases with payroll costs (as evident in groups 1 and 2) but decreases when payroll costs become really high (as evident in groups 3, 4 and 5). The results reported in tables 5.3.7a and 5.3.7c are partly consistent with Capron (1999), Shleifer and Summers (1988) and Gugler and Yurtoglu (2004) who argue that M&A is an effective way of restructuring firms with high payroll burdens (at least, in Europe). This is because a new management team is less likely to uphold existing employee contracts. The results also support the argument that the acquisition of companies with a high payroll cost to sales ratio provides bidder management with an opportunity to create operational synergies through layoffs. Finally, the results are in line with the suggestion that at very high levels, payroll costs can act as a deterrent to takeovers due to implicit costs associated with restructuring. Overall, the results are consistent with the findings in table 5.3.7a – an inverse U-shaped relationship between takeover probability and payroll burden.

5.3.8 Share repurchases hypothesis

The share repurchase hypothesis argues that the presence of share repurchases activity either increases or decreases a firm's takeover likelihood, depending on the predominant role (e.g., managerial signalling, takeover defence tactic, free cash flow distribution, capital structure adjustment) of share repurchase activity. These hypotheses are fully discussed in section 3.3.8. The sign of the relationship will, perhaps, shed light on the predominant motives for share repurchases. The sample employed in this study has a total of 191 share repurchase announcements. Of these 191 announcements, 9.94% or 19 announcements are subsequently followed by takeover bids while 90.05% or 172 announcements are associated with no bids over the next year[161].

The results of the multivariate analysis are shown in table 5.3.8. As shown in table 5.3.8, the announcement of share repurchases activity increases a firm's takeover probability in the next period. The coefficient of the share repurchase variable is positive and significant at the 1% level in model 8A. This finding supports the proposition that share repurchases activity predominantly plays a signalling role. However, the relationship is not robust to different model specifications and controls.

[161] Thomson OneBanker defines a repurchase as 'deals in which a company buys back its shares in the open market or in privately negotiated transactions or a company's board authorises the repurchase of a portion of its shares'. The number of share repurchases reported by Thomson OneBanker is very low as it relies on other databases for the collection of repurchase data and does not collect the data directly from companies. There is a high likelihood that the data provided is incomplete. This represents a weakness in the empirical analysis and an opportunity for further research using alternative more comprehensive data sources.

Table 5.3.8: The relationship between Share repurchases and takeover probability
Panel A: Regression results with robust standard errors

Hypotheses	Proxies	8A	8B	8C
Share repurchase	SRDummy (+/-)	0.737***	0.129	0.110
Inefficient	Profit (-)		0.060	0.054
Management	ADAR (-)		-83.304***	-82.219***
Underval.	BTM(+)		-0.120*	-0.088
GR	S. Growth (+/–)		-0.073	-0.0723
Mismatch	Liquidity (+/–)		-0.608**	-0.556*
	Leverage (+/–)		0.043	0.040
	GRDummy (+)		-0.030	-0.040
Industry Dist.	IDummy (+)		-0.008	-0.024
Free Cash Flow	FCF(+)		0.907***	0.875***
Tangible assets	PPP/TA(+)		0.517***	0.479***
Firm Size	Ln TA (+)		0.040**	0.048***
Firm Age	Age (-)		-0.003***	-0.003**
Constant Term		-2.970***	-3.498***	-3.740***
Industry dummies		NO	NO	YES
Observations		32,363	16,854	16,854
Deviance(–2LL)		12,944	7,205	7,196
Pseudo-R^2		0.000	0.006	0.007
LR Test of Coefficients		7.593***	105.695***	124.070***

Panel B: Regression results with clustered robust standard errors

Hypotheses	Proxies	Model 8D (Firm)	Model 8E (Year)	Model 8F (Industry)
Share repurchase	SRDummy (+/-)	0.129	0.129	0.129
Control variables (in model 8B)		YES	YES	YES
Constant		YES	YES	YES

Notes: The table presents the results of logit regression analysis where the dependent variable is takeover probability (bivariate), the independent variable is share repurchases (SRDummy) and the control variables are the old prediction hypotheses. Profitability is the ratio of EBITDA to total capital employed. ADAR is the average daily abnormal return. Book to market (BTM) is the ratio of book value of equity to market value of equity. Sales growth is the rate of change in total revenues from the previous period. Liquidity is the ratio of cash and short term investments to total assets. Leverage is the ratio of total debt to total equity. GRDummy takes a value of 1 when there is a mismatch between a firm's growth opportunities and its resources and a value of 0 otherwise. IDummy takes a value of 1 if a takeover occurs in a firm's industry and a value of 0 otherwise. FCF/TA is the ratio of free cash flow (operating cash flow less capital investments) to total assets. PPE/TA is the ratio of tangible assets (property, plant and equipment) to total assets. Firm size is the natural log of total assets. Age is the number of years since incorporation. The hypothesised sign is shown in brackets (e.g., (+), (-)). Model 8A represents a univariate logit regression model where the dependent variable is takeover probability and the independent variable is SRDummy, with no control variables. Model 8B and 8C are multivariate logit models with SRDummy as the independent variable and all the old variables as control variables, regressed on firm takeover probability. Model 8C is similar to 8B but also controls for industry using industry dummies (see table 4.2.2 for industry classifications). Models 8D, 8E and 8F are equivalent to model 8B adjusted for firm, year and industry clustering, respectively. 'Observations' is size of the sample used in the analysis, deviance is the -2 log likelihood ratio of the model and the test of model coefficient is the Chi Square test. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

The results partly support the contention that managers are more likely to engage in repurchase programmes when they believe that their shares are undervalued. This share repurchases programme, incidentally, signals the availability of significant free cash flow resources and a lack of suitable future investment projects, as well as the likelihood that the repurchasing firm is undervalued[162]. As shown by the results (table 5.3.8), this signal increases the firm's takeover likelihood. These results are also consistent with the finding that firms gain significant abnormal returns from repurchase announcements (see, for example, Vermaelen (1981), Comment and Jarrell (1991), Ikenberry et al. (1995), Grullon and Michaely (2004), and Peyer and Vermaelen (2005)), as these abnormal returns can partly be due to the increased likelihood that such firms will eventually receive takeover bids. The evidence does not fully support the contention that share repurchases constitute a dependable takeover defence tactic (Harris and Raviv (1988), Bagwell (1991) and Persons (1994)) as the likelihood of receiving a bid is higher for firms with share repurchases activity.

5.3.9 Asymmetric valuation hypothesis

The asymmetric valuation hypothesis predicts that takeover likelihood will decrease with the level of information asymmetry. The degree of firm-level information asymmetry is proxied by a firm's residual volatility in daily stock abnormal returns in the year to June 30th. If the hypothesis is supported, on average, targets should have a lower residual volatility when compared to non-targets. Takeover probability should also decline with residual volatility. This hypothesis is fully discussed in section 3.3.9. The results in table 5.2.1 show that targets (non-targets) have an average residual volatility of 0.0165 (0.0171) – the two figures are rounded to 3 decimal places in the table. The difference in residual volatility (of 0.0014) is not significant at the 10% level.

The median residual volatility for both targets and non-targets is 0.014 and 0.013. The median test shows that there is a significant (at the 5% level) difference of median between targets and non-targets. Table 5.3.9 shows the results from multivariate analysis.

[162] See Bhattacharya (1979), Miller and Rock (1985), Dann (1981), Vermaelen (1981), Vermaelen (1984), Lakonishok and Vermaelen (1990), Hertzel and Jain (1991), Comment and Jarrell (1991) and Dann et al. (1991) for a discussion.

Table 5.3.9: The relationship between residual volatility and takeover probability

Panel A: Regression results with robust standard errors

Hypotheses	Proxies	9A	9B	9C
Asymmetric V.	Residual Vol. (-)	-2.306	-3.564*	-3.652*
Inefficient	Profit (-)		0.050	0.043
Management	ADAR (-)		-86.409***	-85.335***
Underval.	BTM(+)		-0.120*	-0.087
GR	S. Growth (+/–)		-0.077	-0.076
Mismatch	Liquidity (+/–)		-0.598**	-0.547*
	Leverage (+/–)		0.049	0.046
	GRDummy(+)		-0.033	-0.044
Industry. Disturbance	IDummy (+)		-0.022	-0.039
Free Cash Flow	FCF(+)		0.857***	0.822***
Tangible assets	PPP/TA(+)		0.519***	0.481***
Firm Size	Ln TA (+)		0.039**	0.048**
Firm Age	Age (-)		-0.003***	-0.003***
Constant Term		-2.989***	-3.426***	-2.998***
Industry dummies		NO	NO	YES
Observations		25,406	16,854	16,854
Deviance(–2LL)		12,223	7,204	7,195
Pseudo-R^2		0.000	0.006	0.008
LR Test of Coefficients		1.560	108.053***	126.585***

Panel B: Regression results with clustered robust standard errors

Hypotheses	Proxies	Model 9D (Firm)	Model 9E (Year)	Model 9F (Industry)
Asymmetric V.	Residual Vol. (-)	-3.564*	-3.564	-3.564
Control variables (in model 9B)		YES	YES	YES
Constant		YES	YES	YES

Notes: The table presents the results of logit regression analysis where the dependent variable is takeover probability (bivariate), the independent variable is residual volatility the control variables are the old prediction hypotheses. Profitability is the ratio of EBITDA to total capital employed. ADAR is the average daily abnormal return. Book to market (BTM) is the ratio of book value of equity to market value of equity. Sales growth is the rate of change in total revenues from the previous period. Liquidity is the ratio of cash and short term investments to total assets. Leverage is the ratio of total debt to total equity. GRDummy takes a value of 1 when there is a mismatch between a firm's growth opportunities and its resources and a value of 0 otherwise. IDummy takes a value of 1 if a takeover occurs in a firm's industry and a value of 0 otherwise. FCF/TA is the ratio of free cash flow (operating cash flow less capital investments) to total assets. PPE/TA is the ratio of tangible assets (property, plant and equipment) to total assets. Firm size is the natural log of total assets. Age is the number of years since incorporation. The hypothesised sign is shown in brackets (e.g., (+), (-)). Model 9A represents a univariate logit regression model where the dependent variable is takeover probability and the independent variable is residual volatility, with no control variables. Model 9B and 9C are multivariate logit models with residual volatility as the independent variable and all the old variables as control variables, regressed on firm takeover probability. Model 9C is similar to 9B but also controls for industry using industry dummies (see table 4.2.2 for industry classifications). Models 9D, 9E and 9F are equivalent to model 9B adjusted for firm, year and industry clustering, respectively. 'Observations' is size of the sample used in the analysis, deviance is the -2 log likelihood ratio of the model and the test of model coefficient is the Chi Square test. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Consistent with the asymmetry valuation hypothesis, residual volatility has a negative relationship with takeover probability. The coefficient of residual volatility is significant at the 10% level in model 9B and 9C. The relationship is robust when controlled for industry differences using industry dummies as in model 9C. The findings suggest that information asymmetry may deter bidders from making takeover bids for prospective targets. One reason for this (as discussed in section 3.3.9) is that information asymmetry may lead to a systematic reduction in the post-merger value of the combined firm due to the tendency for the bidder to over-pay for the target (when target value is unknown). If this is the case, the level of post-merger value reduction may increase with the level of information asymmetry thus explaining the negative (linear) relationship between information asymmetry and takeover likelihood. The contention – information asymmetry negatively impacts on firm value – is consistent with the findings of prior studies such as Hansen (1987), Krishnaswami and Subramaniam (1999), Martynova and Renneboog (2009)) and Officer et al. (2009). The finding is robust when standard errors are corrected for firm clustering but not for year and industry clustering as shown in panel B[163].

5.3.10 Industry concentration hypothesis

The hypothesis argues that takeover probability will decrease as the concentration of a firm's industry increases, as takeovers are less likely to occur in concentrated industries. This hypothesis is discussed in section 3.3.10. Industry concentration is modelled by the Herfindahl-Hirschman Index (HHI). The index increases as the number of firms within an industry reduces i.e. as the industry becomes more concentrated. The proxy for industry concentration is further discussed in section 3.3.10. The relationship between HHI and takeover probability should be negative (and significant), if the hypothesised relationship is true. The results of the multivariate analysis (logit regression with takeover probability as dependent variable and HHI as independent variable) are presented in table 5.3.10.

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[163] It is worth reiterating that the use of industry dummies controls for unobserved heterogeneity across industries. Standard errors (clustered by industry) control for any correlation between the error terms for firms within the same industry.

Table 5.3.10: The relationship between industry concentration and takeover probability

Panel A: Regression results with robust standard errors

Hypotheses	Proxies	10A	10B	10C	10D
Industry Concentration	HHI (-)	-0.272	-0.957*	-1.150**	-1.413*
Inefficient	Profitability (-)			0.033	0.043
Management	ADAR (-)			-81.792***	-80.917***
Undervaluation	BTM(+)			-0.121	-0.091
GR	S. Growth (+/-)			-0.059	-0.075
Mismatch	Liquidity (+/-)			-0.587*	-0.552*
	Leverage (+/-)			0.037	0.040
	GRDummy (+)			-0.032	-0.041
Industry Dist.	IDummy (+)			0.009	-0.024
Free Cash Flow	FCF(+)			0.891***	0.870***
Tangible assets	PPP/TA(+)			0.573***	0.464***
Firm Size	Ln TA (+)			0.045***	0.050**
Firm Age	Age (-)			-0.003***	-0.003***
Constant Term		-2.862***	-2.917***	-2.920***	-3.676***
Industry dummies		NO	YES	NO	YES
Observations		30,866	30,866	16,851	16,851
Deviance(–2LL)		12,782	12,770	7,196	7,189
Pseudo-R^2		0.000	0.001	0.007	0.008
LR Test of Coefficients		0.923	24.801**	111.860***	126.446***

Panel B: Regression results with clustered robust standard errors

Hypotheses	Proxies	Model 10E (Firm)	Model 10F (Year)	Model 10G (Ind.)
Industry Conc.	HHI (-)	-1.150**	-1.150**	-1.150**
Control variables (in model 10C)		YES	YES	YES
Constant		YES	YES	YES

Notes: The table presents the results of logit regression analysis where the dependent variable is takeover probability (bivariate) and the independent variable is industry concentration proxied by the Herfindahl-Hirschman Index (HHI). The control variables are the old prediction hypotheses. Profitability is the ratio of EBITDA to total capital employed. ADAR is the average daily abnormal return. Book to market (BTM) is the ratio of book value of equity to market value of equity. Sales growth is the rate of change in total revenues from the previous period. Liquidity is the ratio of cash and short term investments to total assets. Leverage is the ratio of total debt to total equity. GRDummy takes a value of 1 when there is a mismatch between a firm's growth opportunities and its resources and a value of 0 otherwise. IDummy takes a value of 1 if a takeover occurs in a firm's industry and a value of 0 otherwise. FCF/TA is the ratio of free cash flow (operating cash flow less capital investments) to total assets. PPE/TA is the ratio of tangible assets (property, plant and equipment) to total assets. Firm size is the natural log of total assets. Age is the number of years since incorporation. The hypothesised sign is shown in brackets (e.g., (+), (-)). Model 10A represents a univariate logit regression model where the dependent variable is takeover probability and the independent variable is HHI, with no control variables. Model 10B, additionally controls for industry using industry dummies. Model 10C and 10D are multivariate logit models with HHI as the independent variable and the old variables as control variables, regressed on firm takeover probability. Model 10D is similar to 10C but also controls for industry using industry dummies (see table 4.2.2 for industry classifications). Models 10E, 10F and 10G are equivalent to model 10C adjusted for firm, year and industry clustering, respectively. 'Observations' is size of the sample used in the analysis, deviance is the -2 log likelihood ratio of the model and the test of model coefficient is the Chi Square test. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

The results from the regression analysis show that there is a negative relationship between takeover probability and industry concentration, as hypothesised. The coefficient of HHI is insignificant in model 10A. This model is a univariate model with no controls for industry differences or other determinants of takeover likelihood. As in model 10B, the coefficient of HHI becomes statistically significant (at the 10% level) when industry differences are controlled for. Taken together, the results suggest that industry concentration on its own (as defined in this study) does not drive takeover activity. In model 10A, the marginal contribution of industry concentration is, possibly, clouded out by noise in the model (e.g., from other determinants of takeover likelihood). Further, the classification method used in this study is, perhaps, too broad to meaningfully capture the industry concentration for close or direct competitors. Model 10B reduces noise in the model by restricting the analysis to broad industry subgroups. The results in model 10B suggest that changes in industry concentration over time, potentially, affect the takeover likelihood of firms within the industry.

Consistent with this argument, model 10C shows that the coefficient of HHI in model 10A becomes significant (at the 5% level) when other determinants of takeover likelihood are added to the model. Model 10D is similar to model 10C but also controls for industry. The results from model 10C confirm that takeover likelihood declines with industry concentration both across firms, industries and time. The results of model 10D (which controls for industry) indicates that the takeover likelihood of firms within an industry declines as the industry's concentration increases over time, and vice versa. The relationship between industry concentration and takeover probability is robust when standard errors are corrected for firm, industry and year as shown in panel B.

The results are in line with Powell and Yawson (2005) who suggest that low concentration industries are more likely to see higher takeover activity. The findings extend the cross-sectional results of Powell and Yawson (2005) by showing that within an industry, takeover likelihood increases as the concentration of firms within that industry decreases over time, and vice versa. The results also support the contention that competition in low concentration industries and antitrust protection in high concentration industries can shape the likelihood of takeovers occurring within these industries. This is further discussed in section 3.3.10.

5.3.11 Market liquidity hypothesis

The market liquidity hypothesis predicts that more takeovers are likely to be witnessed in periods of high market liquidity. In this study, market liquidity is measured as the difference between the London Interbank Offer Rate (LIBOR) and the Bank of England Base Rate (BOEBR). The LIBOR represents the rate at which major financial institutions lend to each other and to other major firms while the BOEBR represents the interest rate charged by the Bank of England (BOE) for overnight lending to financial institutions. A significant spread between the LIBOR and the BOEBR (i.e., low market liquidity) may arise in situations where banks are unwilling to lend to each other due to uncertainties in the market. Firms requiring investment capital (e.g., financing for M&A activity) can more easily obtain finance at good rates when the LIBOR rate is low (i.e., spread between BOEBR and LIBOR is small). Hence, more takeover activity can be expected during such periods. The hypothesis is further discussed in section 3.3.11. Table 5.3.11 presents the results of logit regression analysis between takeover probability and market liquidity.

The results show that as hypothesised, a firm's takeover likelihood increases with increased market liquidity. That is, takeover likelihood increases as the spread between LIBOR and BOEBR reduces. The relationship between market liquidity and takeover probability is robust when standard errors are corrected for firm, industry and year as shown in panel B. The coefficient of the market liquidity measure is negative and significant across all model specifications[164]. In essence, as the market becomes more liquid, funds become more available and firms can access funds more cheaply and easily, corporate investments in the form of takeovers are more likely to be undertaken. The results are consistent with Harford (2005) who finds that merger waves occur in periods of high market liquidity, and argues that market liquidity, indeed, triggers merger waves.

[164] The coefficient of the market liquidity variable is significant at the 1% level when other key factors driving takeover likelihood are controlled for.

Table 5.3.11: The relationship between market liquidity and takeover probability
Panel A: Regression results with robust standard errors

Hypotheses	Proxies	11A	11B	11C	11D
Market Liquidity	LIBOR-BOEBR (-)	-0.090**	-0.084**	-0.235***	-0.229***
Inefficient	Profit (-)			0.055	0.051
Management	ADAR (-)			-82.240***	-81.229***
Underval.	BTM(+)			-0.117*	-0.085
Growth	S. Growth (+/-)			-0.080	-0.081
resource	Liquidity (+/-)			-0.619**	-0.569**
mismatch	Leverage (+/-)			0.043	0.041
	GRDummy (+)			-0.029	-0.040
Industry Dist.	IDummy (+)			-0.015	-0.032
Free Cash Flow	FCF(+)			0.923***	0.893***
Tangible assets	PPP/TA(+)			0.498***	0.456***
Firm Size	Ln TA (+)			0.042***	0.050***
Firm Age	Age (-)			-0.003***	-0.003***
Constant Term		-2.898***	-2.956***	-3.430***	-3.665***
Industry dummies		NO	YES	NO	YES
Observations		32,363	32,335	16,854	16,854
Deviance(−2LL)		12,946	12,922	7,201	7,201
Pseudo-R^2		0.000	0.001	0.007	0.008
LR Test of Coefficients		4.116**	43.288***	114.255***	132.196***

Panel B: Regression results with clustered robust standard errors

Hypotheses	Proxies	Model 11E (Firm)	Model 11F (Year)	Model 11G (Ind.)
Market Liquidity	LIBOR-BOEBR (-)	-0.235***	-0.235**	-0.235***
Control variables (in model 11C)		YES	YES	YES
Constant		YES	YES	YES

Notes: The table presents the results of logit regression analysis where the dependent variable is takeover probability (bivariate) and the independent variable market liquidity proxied by the spread between the LIBOR and the Bank of England base rate (LIBOR-BOEBR). The control variables are the old prediction hypotheses. Profitability is the ratio of EBITDA to total capital employed. ADAR is the average daily abnormal return. Book to market (BTM) is the ratio of book value of equity to market value of equity. Sales growth is the rate of change in total revenues from the previous period. Liquidity is the ratio of cash and short term investments to total assets. Leverage is the ratio of total debt to total equity. GRDummy takes a value of 1 when there is a mismatch between a firm's growth opportunities and its resources and a value of 0 otherwise. IDummy takes a value of 1 if a takeover occurs in a firm's industry and a value of 0 otherwise. FCF/TA is the ratio of free cash flow (operating cash flow less capital investments) to total assets. PPE/TA is the ratio of tangible assets (property, plant and equipment) to total assets. Firm size is the natural log of total assets. Age is the number of years since incorporation. The hypothesised sign is shown in brackets (e.g., (+), (-)). Model 11A represents a univariate logit regression model where the dependent variable is takeover probability and the independent variable is (LIBOR–BOEBR), with no control variables. Model 11B, additionally controls for industry using industry dummies. Model 11C and 11D are multivariate logit models with (LIBOR–BOEBR) as the independent variable and the old variables as control variables, regressed on firm takeover probability. Model 11D is similar to 11C but also controls for industry using industry dummies (see table 4.2.2 for industry classifications). Models 11E, 11F and 11G are equivalent to model 11C adjusted for firm, year and industry clustering, respectively. 'Observations' is size of the sample used in the analysis, deviance is the -2 log likelihood ratio of the model and the test of model coefficient is the Chi Square test. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

5.3.12 Market economics hypothesis

The market economics hypothesis predicts that takeover activity is likely to increase with positive market performance due to the positive sentiment and confidence that results from market growth (proxied by the one-year change in the FTSE All Share index - FTSEChange). This hypothesis builds on the merger wave literature showing that more merger deals are completed during periods of high stock market valuation (Shleifer and Vishny (2003) and Dong et al. (2006)) and that merger activity generally increases in periods of economic growth (Maksimovic and Phillips (2001) and Harford (2005)). This hypothesis is further discussed in section 3.4.12. Table 5.3.12 shows results from the test of this hypothesis.

The results from the logit regression analysis show that market growth (which potentially creates a positive market sentiment, as hypothesised) increases the likelihood for firms to engage in M&A activity. The coefficient of the market sentiment variable is statistically significant at the 1% level. These results are robust (statistically significant at the 1% level) when other determinants of takeover probability are controlled for. The relationship is robust when standard errors are corrected for firm, industry and year as shown in panel B. These results are consistent with prior empirical evidence (see, for example, Maksimovic and Phillips (2001), Shleifer and Vishny (2003), Harford (2005) and Dong et al. (2006)). As discussed in section 3.4.12, this relationship might be attributed to the relative ease of justifying takeover activity in growth periods, the desire to benefit from transitory economic growth and the potential for increased profitability from takeover activity during periods of market growth.

Table 5.3.12: The relationship between market performance and takeover probability

Panel A: Regression results with robust standard errors

Hypotheses	Proxies	12A	12B	12C	12D
Market Economics	FTSEChange(+)	0.930***	0.911***	0.815***	0.815***
Inefficient	Margin (-)			-0.007	-0.012
Management	ADAR (-)			-76.641***	-75.519***
Underval.	BTM(+)			-0.107*	-0.074
Growth	S. Growth			-0.085	-0.087
resource	Liquidity			-0.634**	-0.584**
mismatch	Leverage			0.047	0.044
	GRDummy (+)			-0.035	-0.046
Industry Dist.	IDummy (+)			0.031	0.015
Free Cash Flow	FCF(+)			0.923***	0.892***
Tangible assets	PPP/TA(+)			0.462**	0.417**
Firm Size	Ln TA (+)			0.046***	0.054***
Firm Age	Age (-)			-0.003***	-0.003***
Constant Term		-2.992***	3.051***	-3.632***	-3.877***
Industry dummies		NO	YES	NO	YES
Observations		32,363	16,854	16,854	16,854
Deviance(–2LL)		12,929	12,906	7,196	7,187
Pseudo-R^2		0.001	0.002	0.007	0.008
LR Test of Coefficients		37.679***	75.561***	123.552***	141.860***

Panel B: Regression results with clustered robust standard errors

Hypotheses	Proxies	Model 12E (Firm)	Model 12F (Year)	Model 12G (Ind.)
Market Economics	FTSEChange(+)	0.815***	0.815***	0.815***
Control variables (in model 12C)		YES	YES	YES
Constant		YES	YES	YES

Notes: The table presents the results of logit regression analysis where the dependent variable is takeover probability (bivariate) and the independent variable market performance proxied by the performance of the FTSE All share index. The control variables are the old prediction hypotheses. Profitability is the ratio of EBITDA to total capital employed. ADAR is the average daily abnormal return. Book to market (BTM) is the ratio of book value of equity to market value of equity. Sales growth is the rate of change in total revenues from the previous period. Liquidity is the ratio of cash and short term investments to total assets. Leverage is the ratio of total debt to total equity. GRDummy takes a value of 1 when there is a mismatch between a firm's growth opportunities and its resources and a value of 0 otherwise. IDummy takes a value of 1 if a takeover occurs in a firm's industry and a value of 0 otherwise. FCF/TA is the ratio of free cash flow (operating cash flow less capital investments) to total assets. PPE/TA is the ratio of tangible assets (property, plant and equipment) to total assets. Firm size is the natural log of total assets. Age is the number of years since incorporation. The hypothesised sign is shown in brackets (e.g., (+), (-)). Model 12A represents a univariate logit regression model where the dependent variable is takeover probability and the independent variable is FTSEChange, with no control variables. Model 12B, additionally controls for industry using industry dummies. Model 12C and 12D are multivariate logit models with FTSEChange as the independent variable and the old variables as control variables, regressed on firm takeover probability. Model 12D is similar to 12C but also controls for industry using industry dummies (see table 4.2.2 for industry classifications). 'Observations' is size of the sample used in the analysis, deviance is the -2 log likelihood ratio of the model and the test of model coefficient is the Chi Square test. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

5.3.13 Summary

This section has presented empirical results for tests of the new hypotheses discussed in section 3.4. The methodology underlying these analyses is fully discussed in section 4.3. I find empirical evidence to support seven of the eleven new takeover prediction hypotheses. The empirically validated hypotheses include: (new) firm size, capital structure, payroll synergies, share repurchases, industry concentration, market liquidity and market economics hypotheses. As hypothesised (see section 3.4.2), the smallest and largest firms have the lowest takeover likelihood. The multivariate analyses confirm the existence of an inverse U-shaped relationship between firm size and takeover probability. Similarly, the multivariate analysis lends empirical support to the hypothesised inverse U-shaped relationship between leverage and takeover probability. In line with the payroll synergies hypothesis, the results confirm that takeover probability has a U-shaped relationship with payroll burden. As anticipated, the relationship between share repurchase activity and takeover likelihood is non-zero. The evidence on share repurchases is consistent with the undervaluation and free cash flow signalling perspective of the share repurchase hypothesis (discussed in section 3.4.8). The empirical evidence also suggests that, as hypothesised, industry concentration reduces a firm's takeover likelihood. The evidence also affirms the validity of the market liquidity hypothesis and the market economics hypothesis, as market liquidity and market performance increase the propensity for firms to engage in M&A activity.

Notwithstanding, the empirical evidence does not fully support four of the eleven new hypotheses. These include: financial distress, firm lifecycle, asymmetric valuation and merger rumour hypotheses. The evidence on the financial distress hypothesis is inconclusive. While Taffler Z score does not appear to significantly affect takeover probability, there is some evidence that highly distressed firms are less likely to receive takeover bids. The hypothesised U-shaped relationship between age and takeover likelihood (the firm lifecycle hypothesis) is not empirically supported. While young firms appear to have a high takeover likelihood, there is no evidence that old firms are also susceptible to takeovers. In line with the M&A rumours hypothesis, the presence of rumours appears to increase a firm's takeover likelihood. Nonetheless, this relationship is statistically insignificant when other drivers of takeover likelihood are included in the model. This is despite no significant correlation between the takeover rumour dummy and any of the other independent variables. Similarly, consistent with the asymmetric valuation hypothesis, the relationship between R&D intensity and takeover probability is negative but not statistically significant across all models. The results suggest that the asymmetric valuation and merger rumour hypotheses are valid but do not have residual predictive ability after other drivers of takeover likelihood are controlled for. The next section evaluates the potential contribution of the new variables in a takeover prediction model.

5.4 Assessing the impact of the outlier elimination procedure on the results in sections 5.2 and 5.3.

5.4.1 Overview

The data used in the analyses in sections 5.2 and 5.3 was winsorised at the 5th and 95th percentile to control for the presence of outliers in the raw data obtained from DataStream. The outlier elimination procedure and the quality of the data are discussed in sections 4.2.6. In section 4.2.6, it was concluded that the extreme values (outliers) were actual observations and were not due to errors in DataStream. These outliers were eliminated from the data set by winsorising the affected variables at the 5th and 95th percentiles. As a robustness check, I consider the impact of the winsorisation procedure (5th and 95th) by also looking at the results obtained if a less extensive winsorisation procedure (1st and 99th) is adopted. I review the impact on the descriptive statistics in section 5.4.2, old hypothesis in sections 5.4.3 and new hypothesis in section 5.4.4. As noted in sections 4.6.2, all dummy variables (such as LMDummy, NBVDummy, GRDummy, IDummy, SRDummy, MRDummy), industry variables (Herfindahl index) and market variables (such as FTSEChange and LIBOR-BORBR) are excluded from the winsorisation process. Firm size (natural log of total assets) and firm age (number of years since incorporation) are also not winsorised as no apparent extreme values are observed. I do not therefore discuss the effect of the winsorisation procedure on hypotheses proxied by these variables.

5.4.2 Descriptive statistics

Table 5.4.2 compares the descriptive statistics for each firm-level hypothesis (and proxy) for targets (denoted by ‘1’) and non-targets (denoted by ‘0’). The data used in this table is winsorised at the 1st and 99th percentile. The results in this table can directly be compared to those in table 5.2.1 which employs data winsorised at the 5th and 95th percentile. The main effect of using a less extensive winsorising procedure is the presence of, seemingly, extreme observations as can be seen from the lower (higher) minimum (maximum) values. The quartiles (25th percentile, median and 75th percentile) of the distribution are only marginally affected. The conclusions for the difference in mean and median tests, as well as the results for the Mann Whitney U test are unaffected.

Table 5.4.2: Descriptive Statistics for proxies of management inefficiency, firm undervaluation and growth-resource mismatch

Hypothesis			N Valid	Mean	Mean Diff. (Sig)	MWU U (Sig.)	Std. Dev	Skewness	Min	Max	25th Percentile	Median	Median Diff. (Sig)	75th Percentile
Inefficient	Profitability	0	30,728	0.056			0.638	-2.262	-3.660	2.444	-0.003	0.118		0.232
managmt		1	1,635	0.117	-0.060***	**	0.466	-1.815	-3.660	2.444	0.040	0.121	-0.003	0.219
	ADAR	0	24,232	0.0001			0.002	-0.276	-0.006	0.006	-0.001	0.0002		0.001
		1	1,635	-0.0003	0.0004***	***	0.002	-0.469	-0.006	0.006	-0.001	-0.0001	0.0001***	0.001
Under	BTM	0	26,045	0.505			1.000	1.288	-3.375	5.578	0.123	0.372		0.751
valuation		1	1,541	0.450	0.056***		0.749	0.431	-3.375	5.578	0.128	0.379	-0.007	0.754
Growth	Sales	0	26,893	0.299			1.040	5.383	-0.876	7.928	-0.026	0.090		0.266
resource	growth	1	1,566	0.289	0.011		1.024	5.793	-0.876	7.928	-0.014	0.082	0.009**	0.235
mismatch	Liquidity	0	30,708	0.158			0.202	1.998	0.014	0.930	0.023	0.082		0.205
		1	1,635	0.122	0.037***	***	0.159	2.445	0.000	0.930	0.020	0.067	0.015***	0.154
	Leverage	0	30,714	0.486			1.455	2.178	-5.301	9.180	0.016	0.263		0.651
		1	1,634	0.614	-0.128***	***	1.499	2.580	-5.301	9.180	0.068	0.365	-0.102***	0.740

Notes: The table presents the descriptive statistics for key variables and compares the results for targets to those of non-targets. The hypotheses and their proxies are shown in the first two columns. Profitability is the ratio of EBITDA to total capital employed, ADAR is the average daily abnormal return, book to market is the ratio of book value of equity to market value of equity, Sales growth is the rate of change in total revenues from the previous period, Liquidity is the ratio of cash and short term investments to total assets and Leverage is the firm's debt to equity ratio. In the third column, '0' indicates the results for non-targets and '1' indicates the results for targets. Mean difference for each variable is the difference between the mean for non-targets and targets prior to rounding-up. MWU (U-test) generates the U statistic and the level of significance of U. U (sig) shows the U statistic obtained (and the level of significance of U) when testing whether there is a difference in the distribution of a variable for targets and non-targets. The Median Diff (sig.) shows the difference in median between targets and non-targets for each variable (and its level of significance). *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 5.4.2 cont'd: Descriptive statistics for proxies of asymmetric valuation, tangible assets, free cash flow and financial distress

Hypothesis			N Valid	Mean	Mean Diff.	MWU U	Std. Dev.	Skewness	Min	Max	25th Percentile	Median	Median Diff.	75th Percentile
Asymm.	Residual	0	24,232	0.025			0.017	1.770	0.005	0.095	0.013	0.020		0.031
Valuation	Volatility	1	1,174	0.0244	0.001		0.015	1.977	0.005	0.095	0.015	0.020	-0.000**	0.029
Tangible	PPE/TA	0	30,471	0.311			0.253	0.758	0.000	0.937	0.093	0.264		0.460
property		1	1,634	0.341	-0.030***	***	0.264	0.631	0.000	0.937	0.111	0.294	-0.030***	0.513
FCF	FCF/TA	0	23,693	-0.072			0.323	-3.682	-2.020	0.334	-0.090	0.008		0.071
		1	1,467	0.001	-0.071***	***	0.163	-3.597	-2.020	0.334	-0.044	0.023	-0.015***	0.078
Payroll	HR cost	0	22,234	0.561			1.519	6.739	0.031	12.823	0.165	0.265		0.405
synergies	to sales	1	1,338	0.434	0.127***		1.181	9.146	0.031	12.823	0.168	0.257	0.008	0.381
	ZSCORE	0	25,877	73.559			321.709	6.574	-63.432	2623.100	2.076	8.212		20.499
		1	1,459	57.510	16.049**	**	268.485	7.668	-63.432	2623.100	2.195	7.434	0.778***	16.834

Notes: The table presents the descriptive statistics for key variables and compares the results for targets to those of non-targets. The hypotheses and their proxies are shown in the first two columns. Residual volatility (a proxy of the asymmetric valuation hypothesis) is computed from the firm's one-year daily abnormal returns, PPE/TA is the ratio of tangible assets (property, plant and equipment) to total assets, FCF/TA is the ratio of free cash flow (operating cash flow less capital investments) to total assets, HR cost to sales is the ratio of payroll expenses to total revenue, Age is the number of years since incorporation and ZSCORE is the firm's Taffler Z score. In the third column, '0' indicates the results for non-targets and '1' indicates the results for targets. Mean difference for each variable is the difference between the mean for non-targets and targets prior to rounding-up. MWU (U-test) generates the U statistic and the level of significance of U. U (sig) shows the U statistic obtained (and the level of significance of U) when testing whether there is a difference in the distribution of a variable for targets and non-targets. The Median Diff (sig.) shows the difference in median between targets and non-targets for each variable (and its level of significance). *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

The difference in the BTM between targets and non-targets becomes statistically more significant with targets having a lower BTM ratio when compared to non-targets. The difference in Z Score also substantially increases although the level of significance in the difference in mean test does not change. Overall, the results from table 5.4.2 confirm that the conclusions drawn in sections 5.2 and 5.3 are robust to the winsorisation procedure adopted (5^{th} and 95^{th} percentile). That is, a less extensive winsorisation procedure (1^{st} and 99^{th} percentile) does not change any of the conclusions from the univariate analysis.

5.4.3 Data winsorisation and hypothesis evaluation: Old hypothesis

In this section, I discuss the effect of the winsorising procedure (5^{th} and 95^{th} percentile) on the results of the multivariate analysis – test of old hypotheses. In table 5.4.3, I present the results obtained when a less extensive winsorisation procedure (1^{st} and 99^{th} percentile) is adopted. This table can directly be compare with table 5.2.1b which presents results obtained when a more extensive winsorising procedure (5^{th} and 95^{th} percentile) is adopted.

Table 5.4.3: Pooled regression results for existing hypotheses
Panel A: Robust (Huber-White) Standard errors

Hypotheses	Proxies	Model 13A	Model 13B	Model 13C
Inefficient	Profitability (-)	0.168***	0.057	-0.019
Management	LMDummy (+/-)	-0.424***	-	-0.216**
	ADAR (-)	-98.636***	-117.836***	-120.842***
Undervaluation	BTM (+)	-0.059**	-0.027	-0.034
	NBVDummy (+/-)	0.023	-	-0.031
Growth-resource	Sales Growth (+/-)	-0.010	0.004	0.006
Mismatch	Liquidity (+/-)	-1.215***	-0.507**	-0.443**
	Leverage (+/-)	0.055***	0.029	0.029
	GRDummy (+)	0.026	0.005	-0.005
Industry Dist.	IDUMMY (+)	-0.097	-0.008	-0.023
Firm Size	Ln Assets (-)	0.094***	0.017	0.011
Free Cash Flow	FCF (+)	1.539***	1.059***	0.960***
Tangible assets	PPP/TA (+)	0.458***	0.462***	0.447***
Firm Age	Age (-)	-0.001	-0.003***	-0.003***
Constant Term			-3.506***	-2.696***
Industry dummies		NO	NO	NO
Usable Observations			16,854	16,854
Deviance (–2LL)			7,206	7,202
Pseudo-R^2			0.006	0.007
LR Test of Coefficients			105.550***	113.290***

Panel B: Robust standard errors adjusted for firm, year and industry clustering

Hypotheses	Proxies	Model 13D (firm)	Model 13E (Year)	Model 13F (Industry)
Inefficient	Profitability (-)	-0.019	-0.019	-0.019
Management	LMDummy (+/-)	-0.216**	-0.216**	-0.216*
	ADAR (-)	-120.842***	-120.842***	-120.842***
Undervaluation	BTM (+)	-0.034	-0.034	-0.034
	NBVDummy (+/-)	-0.031	-0.031	-0.031
Growth-resource	Sales Growth (+/-)	0.006	0.006	0.006
Mismatch	Liquidity (+/-)	-0.443**	-0.443*	-0.443*
	Leverage (+/-)	0.029	0.029	0.029
	GRDummy (+)	-0.005	-0.005	-0.005
Industry Dist.	IDUMMY (+)	-0.023	-0.023	-0.023
Firm Size	Ln Assets (-)	0.011	0.011	0.011
Free Cash Flow	FCF (+)	0.960***	0.960***	0.960***
Tangible assets	PPP/TA (+)	0.447***	0.447***	0.447**
Firm Age	Age (-)	-0.003***	-0.003***	-0.003**
Constant Term		-2.696***	-2.696***	-2.696***
Usable Observations		16,854	16,854	16,854
Deviance (–2LL)		7,146	7,144	7,146
Pseudo-R^2		0.016	0.016	0.016
LR Test of Coefficients		98.94***	440.16***	98.94***

Notes: The table presents the results of logit regression analysis where the dependent variable is takeover probability (bivariate) and the independent variable are the old prediction hypotheses. The hypothesis being tested is shown in the first column and its associated proxy is shown in the second column. Profitability is the ratio of EBITDA to total capital employed. LMDummy takes a value of 1 when a firm makes a loss in a given year and a value of 0 otherwise. ADAR is the average daily abnormal return. Book to market (BTM) is the ratio of book value of equity to market value of equity. NBVDummy takes a value of 1 when the BTM is negative and a value of 0 otherwise. Sales growth is the rate of change in total revenues from the previous period. Liquidity is the ratio of cash and short term investments to total assets. Leverage is the firm's debt to equity ratio. GRDummy takes a value of 1 when there is a mismatch between a firm's growth opportunities and its resources and a value of 0 otherwise. IDummy takes a value of 1 if a takeover occurs in a firm's industry and a value of 0 otherwise. Ln Total Assets is the natural log of the firm's total assets. FCF/TA is the ratio of free cash flow (operating cash flow less capital investments) to total assets. PPE/TA is the ratio of tangible assets (property, plant and equipment) to total assets. Age is the number of years since incorporation. The hypothesised sign is shown in brackets (e.g., (+), (-)). Model 13A represents univariate logit regression models where the dependent variable is takeover probability and the sole independent variable is the variable in question (proxy). For example the coefficients of profitability (a proxy for management inefficiency) are obtained from regressing profitability as the sole independent variable with takeover probability as the binary dependent variable (with no control variables). Model 13B is a multivariate logit model which uses all the old variables as independent variables and regresses them on firm takeover probability. Model 13C is a multivariate logit model which uses all the old variables (including LMDummy and NBVDummy) as independent variables and regresses them on firm takeover probability. Model 13D, 13E and 13F are similar to model 13C but the standard errors presented are corrected for firm, year and industry clustering, respectively. 'Usable observations' is size of the sample used in the analysis, deviance is the -2 log likelihood ratio of the model and the test of model coefficient is the Chi Square test. *, **, and *** indicate significance at the 10%, 5% and 1% levels.

As in section 5.4.2 above, the conclusions from the multivariate analysis do not substantially change when a less extensive winsorisation procedure is adopted. I find that all variables maintain their signs (as in table 5.2.1b). With the exception of the BTM variable, all variables maintain their statistical significance. As in table 5.2.1b, the BTM variable is significant in the univariate model (model 13A). Nonetheless, it losses significance (but maintains its size) in the multivariate models (model 13B, 13C, 13D, 13E and 13F).

5.4.4 Data winsorisation and hypothesis evaluation: New hypothesis

In table 5.4.4, I investigate the impact of the winsorisation procedure on the conclusions from the multivariate tests of the new hypotheses. Several of the new hypotheses (including firm size, firm lifecycle, M&A rumours, share repurchases, industry concentration, market liquidity and market economics) are excluded from this robustness check as their associated proxies where not subject to winsorisation. The affected hypotheses include capital structure (panel A), payroll synergies (panel B), financial distress (panel C) and asymmetric valuation (panel D).

The results in table 5.4.4 show that the expected sign of the variables do not change when a less extensive winsorising approach is adopted. Nonetheless, the capital structure and asymmetric valuation hypotheses lose their significance in the multivariate model. The results (and conclusions) for the payroll synergies and financial distress hypotheses do not change.

Table 5.4.4: New hypotheses evaluation: summary of regression results (data winsorised at 1st and 99th percentile)

Proxies (Expected sign)	Model 14A (Univariate)	Model 14B (White)	Model 14C (Industry)	Model 14D (Firm)
Panel A: Capital structure hypothesis				
Leverage (+)	0.091***	0.044*	0.044	0.044*
Leverage squared (-)	-0.006*	-0.003	-0.003	-0.003
Control variables	NO	YES	YES	YES
Constant term	YES	YES	YES	YES
Panel B: Payroll synergies hypothesis				
HR. Cost/Sales (+)	0.726***	1.063**	1.063**	1.063**
HR. Cost/Sales squared (-)	-1.082***	-0.975**	-0.975**	-0.975**
Control variables	NO	YES	YES	YES
Constant term	YES	YES	YES	YES
Panel C: Financial distress hypothesis				
Z Score (-)	-0.000**	-0.000	-0.000	-0.000
ZSDummy (-)	-0.115*	-0.120	-0.120	-0.120
Control variables	NO	YES	YES	YES
Constant term	YES	YES	YES	YES
Panel D: Asymmetric valuation hypothesis				
Residual volatility. (-)	-0.648	-2.819	-2.819	-2.819
Control variables	NO	YES	YES	YES
Constant term	YES	YES	YES	YES

Notes: 14A model with no control variables, 14B model with control variables. Control variables include all variables in model 1B (section 5.2.1). These include profitability, ADAR, BTM, sales growth, liquidity, GRDummy, IDummy, Ln total assets, FCF/TA, PPE/TA and age. Profitability is the ratio of EBITDA to total capital employed. LMDummy takes a value of 1 when a firm makes a loss in a given year and a value of 0 otherwise. ADAR is the average daily abnormal return. Book to market (BTM) is the ratio of book value of equity to market value of equity. NBVDummy takes a value of 1 when the BTM is negative and a value of 0 otherwise. Sales growth is the rate of change in total revenues from the previous period. Liquidity is the ratio of cash and short term investments to total assets. Leverage is the firm's debt to equity ratio. GRDummy takes a value of 1 when there is a mismatch between a firm's growth opportunities and its resources and a value of 0 otherwise. IDummy takes a value of 1 if a takeover occurs in a firm's industry and a value of 0 otherwise. Ln assets is the natural log of the firm's total assets. FCF/TA is the ratio of free cash flow (operating cash flow less capital investments) to total assets. PPE/TA is the ratio of tangible assets (property, plant and equipment) to total assets. Age is the number of years since incorporation. The hypothesised sign is shown in brackets (e.g., (+), (-)). Standard errors in model 14B are heteroschedastic-consistent (Huber-White standard errors). Model 14C and 14D are similar to model 14B but employs robust standard errors corrected for industry and firm clustering (Rogers standard errors). *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

5.4.5 Summary

This section has reviewed the impact of the winsorisation procedure (5th and 95th percentile) adopted in this study. The effect on the conclusions from the univariate (descriptive statistics) and the multivariate (logit regressions) analyses are investigated in sections 5.4.3 and 5.4.4, respectively. The results suggest that the vast majority of the conclusions are robust to the choice of winsorisation procedure. That is, a less extensive winsorisation procedure does not dramatically affect the results and conclusions from sections 5.2 and 5.3.

5.5 Tests for intertemporal variation in target characteristics

Sections 5.2, and 5.3, focused on identifying the unique characteristics of takeover targets. The analyses in these sections involved the use of a full dataset with observations pulled from the 1988 to 2010 period. Consistent with prior studies, no year dummies are included in the models. As discussed in section 4.3.5, the characteristics of targets can exhibit intertemporal variation as suggested by Powell (1997). That is, the characteristics of targets in one period can be markedly different from the characteristics of targets in another period. This has implications for takeover prediction modelling as intertemporal variation in target characteristics is likely to impact on model stability (hence, its predictive ability) over time. The focus in this section is to determine whether target characteristics significantly change from one period to another. Hence, no analyses are done for non-targets.

The stability of target characteristics over time is evaluated by testing for intertemporal variation using the methodology discussed in section 4.3.5. This methodology is adopted from the test of intertemporal variation proposed by Thomas (1997). The methodology (fully discussed in section 4.3.5) involves comparing the characteristics of targets in one period (period 1) to the characteristics of targets in the next period (period 2) using the logit model shown in equation 4.3.4(1). Here, the dependent variable in the model takes a value of 1 for targets in the second period (period 2) and a value of 0 for targets in the first period (period 1)[165].

Given that the data spans from 1988 to 2009, 20 yearly breakpoints are set from 1989 to 2009. At each breakpoint (e.g., 1994), I investigate whether the characteristics of targets prior to this breakpoint (e.g., 1988–1993) are different from the characteristics of targets after the breakpoint (e.g., 1994–2009) by running the regression model. A significant coefficient for a characteristic (e.g., R&D intensity) in the regression model will indicate that the characteristic (R&D intensity) of targets in one sub-period (e.g., period 1) is different from the characteristic (R&D intensity) of targets in the second sub-period (e.g., period 2). Such a finding will suggest the existence of intertemporal variation and non-stability in the characteristics (e.g., R&D intensity) of targets over time. The results of the analyses are summarised in the table 5.5.1.

[165] All non-targets are excluded from the sample and only targets are considered for this analysis.

Table 5.5.1: The differences in the characteristics of targets over time

Hypotheses	Proxies	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Inefficient Management	Profitability	-	-	-	-	-	-	-	-	-	-	-			
	LMDummy			+					+						
	ADAR		+			+	+	+	+	+	+	+			
Undervaluation	BTM									-	-	-	-	-	-
	NBVDummy				+	+	+	+	+					-	
GR Mismatch	Sales Growth									-			+		
	Liquidity														
	GRDummy					+		-	-		-	-			-
Industry Dist.	IDummy				+	+	+	+	+	+	+	+			
Free Cash Flow	FCF/TA	+	+	+	+	+	+								
Tangible assets	PPP/TA				-	-	-	-	-	-	-	-	-	-	-
Firm Size	Ln Assets				+				-						
	Ln Assets sq.				-				+	+			+		+
Capital Structure	Leverage											+	+	+	
	leverage Sq.											-	-		
Firm life cycle	Age														
	Age sq														
Share Repurchases	SRDummy					-									
M&A Rumours	MRDummy														
Payroll Synergies	HR.Cst/Sales													+	
	HR.Cst/Sales Sq.						+	+							
Financial Distress	Z Score													+	
	ZSDummy									+					
I Concentration	Herf. Index				+	+	+	+	+	+	+	+	+	+	+
Asymmetric valuatn	Residual Vol.			-	-	-	-	-	-	-	-	-	-	-	-
Market Economics	FTSEChange				-	-	-	-	-	-	-		-		-
Market Liquidity	LIBOR-BOEBR			-	-	-	-	-	-	-	-	+	+	+	+
Chi Square Test		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: The table shows the changes in the characteristics of targets over time measured using a multivariate model proposed by Thomas (1997). The sample used is made up of 1,631 takeover targets where bids were announced between 1989 and 2011. Profitability is the ratio of EBITDA to total capital employed. LMDummy takes a value of 1 when a firm makes a loss in a given year and a value of 0 otherwise. ADAR is the average daily abnormal return. Book to market (BTM) is the ratio of book value of equity to market value of equity. NBVDummy takes a value of 1 when the BTM is negative and a value of 0 otherwise. Sales growth is the rate of change in total revenues from the previous period. Liquidity is the ratio of cash and short term investments to total assets. Leverage is the firm's debt to equity ratio. GRDummy takes a value of 1 when there is a mismatch between a firm's growth opportunities and its resources and a value of 0 otherwise. IDummy takes a value of 1 if a takeover occurs in a firm's industry and a value of 0 otherwise. Ln Total Assets is the natural log of the firm's total assets. FCF/TA is the ratio of free cash flow (operating cash flow less capital investments) to total assets. PPE/TA is the ratio of tangible assets (property, plant and equipment) to total assets. Age is the number of years since incorporation. SRDummy takes value of 1 if a firm makes a repurchase announcement in a particular year and a value of 0 otherwise. MRDummy takes value of 1 if a firm is rumoured to be a takeover target in a particular year and a value of 0 otherwise. HR cost to sales is the ratio of total cost of payroll to revenues. Z Score is a firm's Taffler Z score. ZSDummy takes value of 1 if a firm has a negative Z Score in a particular year and a value of 0 otherwise. Herf Index (Herfindahl Index) is a proxy for industry concentration. Residual Vol. (volatility) is the standard deviation of a firm's one year (to June 30th) excess returns. FTSEChange is the performance of the FTSE All Share index over the previous year. LIBOR-BOEBR (a measure of market liquidity) is the spread between the LIBOR and the base rate. In the first regression (column 3 - 1994), for example, the dependent variable takes a value of 1 for all targets between 1994 and 2009 and a value of 0 for all targets between 1988 and 1994 – '1994' is the breakpoint. This procedure is followed for all 20 regression models – for all 20 breakpoints. The greyed-out boxes show that the variable is insignificant (at the 10% level) in the model. The positive sign ('+') or the negative sign ('-') indicate that the variable is positive or negative (respectively) and significant at the 10% level, respectively. The Chi Squared test is a joint test of model coefficients (conducted at the 10% level). A significant Chi Square in the model is denoted by 'Y'.

For simplicity, only the significant changes across time are presented in table 5.5.1. Results for the 1989 – 1993 and 2008 – 2009 breakpoints are not presented as the results are not significant (i.e., there are no intertemporal variations in the characteristics of targets at these breakpoints). The grey boxes in the table indicate that the results (changes in the characteristics of targets) are not statistically significant at the 10% level.

The analyses (e.g., 2000) compare targets in one period (1988–1999) to targets in the second period (2000–2009) in terms of their takeover prediction variables. The question here is whether the variables remain consistent from one period (1988–1999) to another (2000–2009) – hence, no intertemporal variation. A non-significant result for a particular variable (e.g., Ln total assets), indicates that there are no significant differences in the characteristic (size of targets) between the two periods. The Chi Square test (significant at the 10% level) in all periods (1992–2008) reveals that there is some level of intertemporal variation in some of the characteristics of targets over time. That is, the null hypothesis that the coefficients of the independent variables are jointly equal to zero is rejected (for all breakpoints between 1992 and 2008, inclusive).

The results are broadly consistent with Powell (1997) who argues that the characteristics of targets are unstable over time. The results show that targets report higher abnormal returns (ADAR) between 1998 and 2004 and were less profitable prior to 2005. This intertemporal variation in target market performance (ADAR), potentially, explains some of the inconsistency on the relationship between performance and takeover likelihood in empirical research (see Agrawal and Jaffe (2003)). The results also show a general decline in the book to market ratio of targets over time – mainly post-2002. Similarly, the level of liquidity and the proportion of tangible assets for target firms have continuously declined over time. There is also some evidence that, comparatively, targets had more free cash flow and were drawn from less concentrated industries in the first half of the period.

There is, perhaps, no persistent inter-temporal variation in target sales growth, firm size, leverage, share repurchases, rumours, Z score (and Z score dummy) and R&D intensity across time. The changes shown for market economics (FTSEChange) and market liquidity (LIBOR-BOEBR) more adequately capture the changing environmental conditions (not changes in target characteristics). For example, the period post-2004 (leading up to the global financial crises) is linked with an increase in the spread between the LIBOR and the Bank of England base rate. Overall, the results show that, as suggested by Powell (1997), some of the characteristics of targets change slightly over time. I find that the changes are in a single direction implying a high level of stability of the prediction variables over time. The results suggest that short-term takeover prediction models (employing fewer years of data) can, potentially, be better predictive tools. This finding, perhaps, justifies the modelling approach of Espahbodi and Espahbodi (2003) who use data over a short period of six months to develop their model. Nonetheless, the use of short periods (and hence limited data) generates new questions of whether model parameters are sufficiently trained to predict targets out-of-sample, especially in dynamic economic environments. This issue will be further explored in chapter 6.

5.6 Chapter summary and conclusion

The main objective of this chapter was to test and validate both the old and new prediction hypotheses discussed in chapter 3 using the methodologies discussed in chapter 4. A secondary objective of the chapter was to conduct a preliminary empirical analysis to evaluate the stability of target characteristics over time. Table 5.6.1 summarises the results from the empirical tests (univariate, multivariate and robustness checks) of the old and new hypotheses. The results for the old hypotheses are presented in panel A and those for the new hypotheses are presented in panel B. The univariate tests include the difference of means test, median test and U-tests. The multivariate test refers to the results from logit regression analyses (controlling for industry effects). The robustness tests for the old hypotheses (panel A) refer to the results obtained when all the old hypotheses are combined with all the new hypotheses in one model (see model section 6.2 for full details). Additionally, the robust tests for the new hypotheses (panel B) also include the results from 'mean centering' and piecewise regression analyses. In table 5.6.1, 'YES' indicates that the hypotheses is empirically supported (and vice versa) and 'NA' indicates that the test is 'not applicable' to the specific hypothesis.

As summarised in table 5.6.1 (panel A), the evidence empirically validates some of the old hypotheses. The univariate and multivariate analysis lends support to the management inefficiency, free cash flow, tangible assets and firm age hypotheses. However, when the new hypotheses are included in the model (i.e., robustness check), only the management inefficiency, tangible assets and firm age hypotheses are empirically supported. These results fully discussed and further explored in section 6.2.

Table 5.6.1: Summary of validation test results for old and new takeover prediction hypotheses

Hypotheses	Proxies (Expected sign)	Univariate	Multivariate	Robustness
Panel A: Old Hypotheses		**Supported**	**Supported**	**Supported**
Inefficient Management	Profitability (-)	NO	NO	NO
	ADAR (-)	YES	YES	YES
Undervaluation	BTM(+)	NO	NO	NO
Growth Resource Mismatch	Sales Growth (+/-) Liquidity (+/-) Leverage (+/-) GRDUMMY(+)	NA	NO	NO
Industry Disturbance	IDUMMY(+)	NA	NO	NO
Firm Size	Ln Assets (-)	NO	NO	NO
Free Cash Flow	FCF(+)	YES	YES	NO
Tangible assets	PPP/TA(+)	YES	YES	YES
Firm Age	Age (-)	YES	YES	YES
Panel B: New Hypotheses		**Supported**	**Supported**	**Supported**
Firm Size	Ln Assets (+) Ln Assets Sq. (-)	YES	YES	YES
Capital Structure	Leverage (+) Leverage Sq.(-)	NA	YES	YES
Share Repurchases	SRDummy(+/-)	NA	NO	NO
M&A Rumours	MRDummy (+)	NA	NO	NO
Payroll Synergies	HR Cost/Sales (+) HR Cost/Sales. Sq. (-)	NA	YES	YES
Industry Concentration	Herfindahl Index(-)	NA	YES	YES
Asymmetric Valuation	Residual Volatility (-)	NO	YES	NO
Firm Life cycle	Age (-) Age. Squared (+)	NA	NO	NO
Financial Distress	Z Score (-)	YES	NO	NO
	ZSDummy (-)	NA	YES	YES
Market Economics	FTSEChange (+)	NA	YES	YES
Market Liquidity	LIBOR-BOEBR (-)	NA	YES	YES

Notes: The table summarises the results of section 5.2 and 5.3 – tests of old and new hypotheses. 'Univariate' refers to the results from the univariate analysis (t test, U-test and M test). 'Multivariate' refers to the results from the logit regression analysis (including industry controls and mean-centering). 'Robustness' tests for the old hypotheses (panel A) refer to the results obtained when all the old hypotheses are combined with all the new hypotheses in one model. A summary of these results are discussed in section 6.2 'Robustness' tests for the new hypotheses (panel B) additionally include the results from 'mean centering', piecewise regression analyse and standard errors corrected for firm, year and industry clustering. 'YES' ('NO') indicates that the results from the respective test provides (does not provide) support for the hypothesis. 'NA' indicates that the particular test was not applicable or no substantial testing was done.

Profitability is the ratio of EBITDA to total capital employed. ADAR is the average daily abnormal return. Book to market (BTM) is the ratio of book value of equity to market value of equity. Sales growth is the rate of change in total revenues from the previous period. Liquidity is the ratio of cash and short term investments to total assets. Leverage is the firm's debt to equity ratio. GRDummy takes a value of 1 when there is a mismatch between a firm's growth opportunities and its resources and a value of 0 otherwise. IDummy takes a value of 1 if a takeover occurs in a firm's industry and a value of 0 otherwise. FCF/TA is the ratio of free cash flow (operating cash flow less capital investments) to total assets. PPE/TA is the ratio of tangible assets (property, plant and equipment) to total assets. Age is the number of years since incorporation. Ln Assets is the natural log of a firm's total assets. SRDummy takes a value of 1 if a firm announced any share repurchases in the period and a value of 0 otherwise. MRDummy takes a value of 1 if a firm is the target in a merger rumour and a value of 0 otherwise. ZScore is a firm's Taffler Z Score. ZSDummy takes a value of 1 if a firm has a negative Z Score and a value of 0 otherwise. HR Cost to sales is the ratio of payroll expenses to revenues. Herfindahl index is the concentration of the firm's industry in a particular year. Residual volatility is the standard deviation of a firm's abnormal return in the year to June 30th. FTSEChange is the performance of the FTSE All Share index in the year to June 30th. LIBOR-BOEBR is the spread between the LIBOR and the Bank of England's base rate. The hypothesised sign is shown in brackets (e.g., (+), (-)).

I find that takeover likelihood decreases with market (ADAR) performance but increases with accounting performance. Only the first part of the finding (i.e., ADAR and takeover likelihood) is consistent with the management inefficiency hypothesis as discussed in prior research (e.g., Palepu (1986)). The evidence here suggests that targets are profitable firms with low future prospects as opposed to the general contention that targets are inefficiently managed firms. The qualification (i.e., historical profitability) distinguishes takeover targets from the large number of underperforming firms in the population.

The empirical result is inconsistent with the undervaluation hypothesis. On average, targets report lower BTM when compared to non-targets – with takeover probability declining with BTM. Consistent with the firm age hypothesis, the results confirm that takeover probability decreases with firm age. This finding – a negative relationship between age and takeover probability – is further supported by the multivariate analysis. There is empirical support for the free cash flow (FCF) and tangible assets hypotheses as the results show that a firm's takeover likelihood increases with the level of FCF and the level of tangible assets. Nonetheless, the FCF becomes statistically insignificant (i.e., its residual explanatory power diminishes) when the new variables are included in the model. Contrary to the (old) firm size hypothesis, the results are inconsistent with the contention that targets are small firms (Palepu (1986)). The multivariate analysis also shows that takeover probability increases with firm size. Again, the results do not also support the growth resource mismatch and industry disturbance hypotheses.

Section 5.3 discussed the results from the empirical tests of the new hypotheses. The empirical evidence lends some support to the (new) firm size, capital structure, financial distress, payroll synergies, industry concentration, market economics and market liquidity hypotheses. I find empirical support for the share repurchase and merger rumour hypotheses but the residual explanatory power (i.e., statistical significance) of the variables decline when all the other new variables are included in the model. The empirical evidence does not fully support the firm lifecycle hypothesis. As hypothesised, the smallest and largest firms have the lowest takeover likelihood – an inverted U-shaped relationship between firm size and takeover probability. The results also provide empirical support for the capital structure hypothesis. Consistent with the hypothesis, the firms with the highest and lowest levels of leverage face the lowest threat of takeovers. The payroll synergies hypothesis is validated and remains robust to different empirical tests and alternative model specifications. The results confirm that takeover probability has a inverse U-shaped relationship with firm payroll burden. Here, takeover likelihood increases with payroll cost up until a level where payroll costs serve as a takeover deterrent.

The relationship between share repurchase activity and takeover likelihood is positive. In support of the undervaluation and free cash flow signalling perspective (discussed in section 3.3.8), I find that a firm's engagement in repurchase activity increases its takeover likelihood. As hypothesised, industry concentration moderates a firm's takeover likelihood. Firms in low concentration industries are more susceptible to takeovers than firms in high concentration industries. The results show that takeover propensity is not only driven by firm characteristics but also by the prevailing market conditions. For example, I find that market liquidity (market liquidity hypothesis) and market performance (the market economics hypothesis) influence the propensity for firms to engage in M&A activity.

The asymmetric valuation hypothesis is empirically supported. The relationship between residual volatility and takeover probability is negative (as hypothesised) and statistically significant. Nonetheless, the relationship is not robust (when standard errors are corrected for year and industry clustering). I find partial support for the financial distress hypothesis – takeover probability is negatively related to a firm's Taffler Z score. Its residual explanatory power diminishes when other control variables are included in the model. In line with the hypothesis, there is some evidence that highly distressed firms (firms with Z score below zero) are less likely to receive takeover bids. Further, I find no support for the firm lifecycle hypothesis. The results show that the negative relationship between firm age and takeover probability reported across the firm survival literature (e.g., Agarwal and Gort (1996), Jovanovic (1982), Dunne et al. (1989), Audretsch (1991), Loderer and Waelchli (2010)) is only persistent for fairly established firms (firm age between 12 and 164 years). This relationship reverts for a sample of young firms (below 12 years). In line with the M&A rumours hypothesis, the presence of M&A rumours appears to increase a firm's takeover likelihood. Nonetheless, this relationship is statistically insignificant when other determinants of takeover likelihood are added to the model. I attribute some of this lack of statistical validity to the weaknesses in the rumour data collection process.

The old and new variables are combined to develop the new model in chapter 6. The chapter (6) focuses on measuring the performance of the new model when measured against a benchmark model – the old model. Several measures of performance including area under ROC curves and target concentration in out-of-sample tests are explored.

CHAPTER 6 MODEL PREDICTIVE ABILITY

6.1 Overview

The objective of this chapter is to evaluate the predictive power of the new model when compared to a benchmark model – the old model[166]. The development of the new and old models is discussed in section 4.4.2. Key statistics for logit regression models such as pseudo R squares (Cox and Snell R squares, Negelkerke R squares) and area under the ROC curve are initially used as the basis of comparison. In addition, I ascertain model performance by mimicking the real life usage of the model (albeit through 'back-testing') using out-of-sample tests. Out-of-sample (or holdout sample) predictive tests involve testing the model on new data, obtained from the post-estimation period, and not used in the development of the model. Section 6.2 evaluates the empirical relevance of the new variables by comparing the performance of the new model against that of the old model.

In addition to evaluating the model's performance (in section 6.2, 6.3, 6.4), I explore the variations in model performance across different market conditions (in section 6.5). I also evaluate the impact of the length of the estimation period on the model's performance (in section 6.6). Further, I investigate the predictive ability of model parameters for predictions more than one year (and up to ten years) after parameter development (in section 6.7) and I explore the optimal choice of portfolio selection technique (in section 6.8). As will be shown and discussed, these issues (or choices) are important in the development of an optimal prediction strategy. The methodology used for these analyses is fully discussed in section 4.4.

[166] The new model is evaluated by comparing its performance with that of a control or benchmark (described as 'old') model. The old model employs the same dataset and methods as the new model but is restricted to the old variables only. The only difference between the old and new model is the fact that the new model has 15 additional prediction variables (the new variables) as shown in table 4.4.2.

6.2 The empirical relevance of the new variables

6.2.1 Overview of regression results

Section 5.3 tested the validity of the new hypotheses which were discussed in section 3.4. The results (summarised in section 5.3.13) show that the empirical evidence lends some support to eight of the eleven new hypotheses. As discussed in section 4.3.4, the new model is a model which combines the new hypotheses and the old hypotheses under a predictive modelling framework. This section empirically tests the relevance of combining the two sets of variables. It also explores the contribution of the new variables.

In table 6.2.1a, panel A (Models 15A – 15D) presents regression results for the old model (old variable only) and the new model (old and new variables combined). Model 15A represents a logit regression model where the dependent variable is takeover probability and the independent variables are the old prediction hypotheses (old model). Model 15B is similar to model 15A but controls for industry using industry dummies. Model 15C is the new model. It combines the old and new hypotheses. Model 15D is similar to model 15C but controls for industry using industry dummies. The results from chapter 5 revealed that some of the predictor variables do not significant impact on takeover likelihood (at the 10% level). A question arises whether these variables should be excluded from the model. Panel B (model 15E – 15H) explores different versions of the new model. Model 15E is the new model without the new variables which are found to be insignificant (in section 5.3). These variables include Age Squared, MRDummy, SRDummy and ZScore. Model 15E is therefore a clean version of the new model. Model 15F is similar to model 15E but controls for industry differences using industry dummies. Model 15G is a restricted version of the clean new model. It excludes the old hypotheses which are found to be insignificant in the regression analyses in section 5.2 Model 15H replicates 15G but controls for industry differences using industry dummies.

Table 6.2.1a: Empirical relevance of the new variables

Panel A: Regression results from combining old and new variables

Hypotheses	Proxies (Exp. sign)	15A (Old)	15B (Old)	15C (New)	15D (New)
Panel A: Old Hypotheses					
Inefficient	Profitability (-)	0.060	0.054	-0.575**	-0.582**
Management	LMDummy (+/-)			-0.228	-0.228
	ADAR (-)	-83.317***	-82.230***	-82.519***	-81.234***
Undervaluation	BTM (+)	-0.120*	-0.088	-0.199**	-0.165*
	NBVDummy (+/-)			-0.082	-0.104
GR Mismatch	Sales Growth (+/-)	-0.074	-0.073	-0.050	-0.072
	Liquidity (+/-)	-0.605**	-0.554*	-0.442	-0.356
	Leverage (+/-)	0.043	0.040		
	GRDummy (+)	0.030	-0.040	-0.064	-0.067
Industry Dist.	IDummy (+)	-0.008	-0.024	0.078	0.039
Firm Size	Ln Assets (-)	0.040**	0.049***		
Free Cash Flow	FCF (+)	0.908***	0.875***	0.641	0.602
Tangible assets	PPP/TA (+)	0.520***	0.481***	0.454**	0.330*
Firm Age	Age (-)	-0.003***	-0.003**		
Panel B: New Hypotheses					
Firm Size	Ln Assets (+)			2.413***	2.417***
	Ln Assets sq.(-)			-0.062***	-0.062***
Capital Structure	Leverage (+)			0.208	0.243
	Leverage Sq. (-)			-0.061	-0.072
Firm life cycle	Age (-)			-0.007*	-0.007*
	Age sq. (+)			0.000	0.000
S. Repurchases	SRDummy (+/-)			0.222	0.205
M&A Rumours	MRDummy (+)			0.059	0.034
Payroll Synergies	HR. Cost/Sales (+)			1.048*	1.334**
	HR.Cost/Sales Sq. (-)			-1.179**	-1.383**
Financial Distress	Z Score (-)			-0.000	-0.000
	ZSDummy (-)			-0.042	-0.065
I. Concentration	Herf. Index (-)			-0.755	-0.740
Asymmetry	Residual Vol. (-)			-3.250	-3.283
Market Economics	FTSEChange (+)			0.469**	0.483**
Market Liquidity	LIBOR-BOEBR (-)			-0.344***	-0.344***
Constant Term		-3.506***	-3.510***	-25.985***	-25.717***
Industry dummies		NO	YES	NO	YES
Observations		16,854	16,854	14,093	14,093
Deviance(–2LL)		7,153	7,135	5,782	5,766
Cox and Snell's R Square		0.006	0.007	0.014	0.015
Nagelkerke R Square		0.018	0.021	0.039	0.042
Hosmer-Lemeshow GOF (sig.)		3.968	10.418	12.086	12.025
Area under ROC Curve (sig.)		0.599***	0.610***	0.642***	0.648***
LR Test of model coefficients (sig.)		147.006***	166.552***	191.751***	208.372***

Table 6.2.1a: Empirical relevance of the new variables (continued)

Panel B: Regression results for different versions of the new model

Hypotheses	Proxies (Exp.sign)	15E (Clean)	15F (Clean)	15G(Restricted)	15H(Restricted)
Panel A: Old Hypotheses					
Inefficient	Profitability (-)	-0.578**	-0.586**		
Management	LMDummy (+/-)	-0.208	-0.226		
	ADAR (-)	-86.020***	-81.405***	-83.659***	-82.321***
Undervaluation	BTM (+)	-0.203**	-0.169**	-0.126*	-0.083
	NBVDummy (+/-)	-0.073	-0.095		
GR Mismatch	Sales Growth (+/-)	-0.040	-0.062		
	Liquidity (+/-)	-0.438	-0.362	-0.628*	-0.558
	GRDummy (+)	-0.068	-0.072		
Industry Dist.	IDummy (+)	0.080	0.039		
Free Cash Flow	FCF (+)	0.606	0.578	0.456	0.449
Tangible assets	PPP/TA (+)	0.475***	0.348*	0.422	0.295
Firm Age	Age (-)	-0.004***	-0.003**	-0.003**	-0.003**
Panel B: New Hypotheses					
Firm Size	Ln Assets (+)	2.378***	2.386***	2.222***	2.242***
	Ln Assets sq.(-)	-0.061***	-0.061***	-0.056***	-0.057***
Capital Structure	Leverage (+)	0.224	0.236	0.201	0.240
	leverage Sq. (-)	-0.068	-0.080	-0.067	-0.080
Payroll Synergies	HR. Cst/Sales (+)	1.025*	1.312**	1.227**	1.500**
	HR.Cst/SalesSq. (-)	-1.089*	-1.364**	-1.105**	-1.360**
Financial Distress	ZSDummy (-)	-0.046	-0.058	-0.017	-0.037
I. Concentration	Herf. Index (-)	-0.726	-0.728	-0.426	-0.322
Asymmetry	Residual Vol (-)	-3.246	-3.377	-3.341	-3.178
Market Economics	FTSEChange (+)	0.476**	0.482**	0.381*	0.408*
Market Liquidity	LIBOR-BOEBR (-)	-0.345***	-0.345***	-0.357***	-0.350***
Constant Term		-25.597***	-25.731***	-24.409***	-24.714***
Industry dummies		NO	YES	NO	YES
Observations		14,093	14,093	14,549	14,549
Deviance(–2LL)		5,784	5,870	6,036	6,027
Cox and Snell's R Square		0.013	0.015	0.012	0.014
Nagelkerke R Square		0.039	0.042	0.036	0.040
Homer-Lemslow GOF Test (Sig.)		13.565	11.806	7.633	12.281
Area under ROC Curve (Sig.)		0.641***	0.649***	0.636***	0.645***
LR Test of model coefficients (Sig.)		190.290***	207.019***	182.580***	201.044***

Notes to table 6.2.1a: The table presents the results of logit regression analysis where the dependent variable is takeover probability (bivariate), the independent variables are the proxies of the old and new hypotheses. Profitability is the ratio of EBITDA to total capital employed. LMDummy takes a value of 1 when a firm makes a loss and a value of 0 otherwise. ADAR is the average daily abnormal return. Book to market (BTM) is the ratio of book value of equity to market value of equity. NBVDummy takes a value of 1 when a firm's BTM is negative and a value of 0 otherwise. Sales growth is the rate of change in total revenues from the previous period. Liquidity is the ratio of cash and short term investments to total assets. Leverage is the firm's debt to equity ratio. GRDummy takes a value of 1 when there is a mismatch between a firm's growth opportunities and its resources and a value of 0 otherwise. IDummy takes a value of 1 if a takeover occurs in a firm's industry and a value of 0 otherwise. FCF/TA is the ratio of free cash flow (operating cash flow less capital investments) to total assets. PPE/TA is the ratio of tangible assets (property, plant and equipment) to total assets. Age is the number of years since incorporation. Ln Assets is the natural log of a firm's total assets. SRDummy takes a value of 1 if a firm announced any share repurchases in the period and a value of 0 otherwise. MRDummy takes a value of 1 if a firm is the target in a merger rumour and a value of 0 otherwise. ZScore is a firm's Taffler Z Score. ZSDummy takes a value of 1 if a firm has a negative Z Score and a value of 0 otherwise. HR Cost to sales is the ratio of payroll expenses to revenues.

Notes to table 6.2.1a cont'd: Herf. Index (Herfindahl index) is the concentration of the firm's industry in a particular year. Residual volatility is the standard deviation of a firm's abnormal return in the year to June 30th. FTSEChange is the performance of the FTSE All Share index in the year to June 30th. LIBOR-BOEBR is the spread between the LIBOR and the Bank of England's base rate. The hypothesised sign is shown in brackets (e.g., (+), (-)).

Panel A (Models 15A – 15D) presents regression results for the old model and the new model (with all the new variables). Model 15A represents a logit regression model where the dependent variable is takeover probability and the independent variables are the old prediction hypotheses (old model). Model 15B is similar to model 15A but controls for industry using industry dummies. Model 15C is the new model. It combines the old and new hypotheses. Model 15D is similar to model 15C but controls for industry using industry dummies. Industry classifications are discussed in table 4.2.2. Model 15E is the new model without the new variables which are found to be insignificant (in section 5.3). These variables include Age Squared, MRDummy, SRDummy and ZScore. Model 15E is therefore a clean version of the new model. Model 15F is similar to model 15E but controls for industry differences using industry dummies. Model 15G is a restricted version of the clean new model. It excludes the old hypotheses which are found to be insignificant in the regression analyses in section 5.2 Model 15H replicates 15G but controls for industry using industry dummies. 'Observations' is size of the sample used in the analysis, deviance is the -2Log likelihood ratio of the model and the test of model coefficient is the Chi Square test. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively (robust standard errors).

Based on the results in table 6.4.1a, some preliminary conclusions can be drawn. First, by comparing model 15A and 15C (or model 15B and 15D), I find that the inclusion of the new variables in the prediction model leads to a substantial increase in the pseudo R Squares (Cox and Snell and Nagelkerke R squares)[167]. The indication is that the inclusion of the new variables substantially improves the explanatory power of existing prediction models. If the criticisms of pseudo R squared and its interpretation (e.g., see criticisms by Long and Freese (2006)) is set aside for a moment, the reported pseudo R squared are arguably low. Nonetheless, this magnitude of pseudo R squared is consistent with prior literature in takeover likelihood modelling (e.g., Powell (1997, 2001, 2004) and Cremers et al. (2009)). The inclusion of the new variables also substantially reduces the deviance (or -2 log likelihood)[168] of the model. The improvement in pseudo R squares and deviance

167 Pseudo R squares in logistic regressions cannot be interpreted in the same way as R squared in linear regression. While R squared (obtained in linear regressions) measures a model's ability of explaining the variability in the data, pseudo R squares (obtained in nonlinear regressions) simply compares the log likelihood of a null model to that of a full model. Although the pseudo R squared was proposed as a substitute for R squared in nonlinear regressions, its use has been highly criticised by econometricians (e.g., Long and Freese (2006)). Long and Freese (2006) contend that pseudo R-squared only has meaning and relevance when compared to another pseudo R-squared of the same type (e.g. Cox and Snell R.sq, Negelkerke R.sq, McFadden's R.sq), computed from the same data set (e.g. UK public firms) and when the underlying model is predicting the same outcome (e.g. takeover likelihood). It is therefore suitable for comparing two models predicting the same outcome and derived from the same data, as in the case of this study. The pseudo R squared produced by the RATS software is based on the pseudo R squared for dichotomous dependent variables derived by Estrella (1998).

168 The -2 log likelihood test is generally used to compare the fit of two models (model 1 and model 2) when one model (model 1) is nested within the other (model 2). Model 2, in this case, represents the new model, as the old model is nested within it. The probability distribution for -2LL is a Chi

corroborates the observation that the area under the ROC curve increases when the new variables are added to the model (as in panel A). (The results from ROC curve analyses are fully discussed in section 6.2.2.) This suggests that the new variables generally improve the predictive ability of the old model. Hence, the new variables are relevant for prediction modelling.

Second, the p–values of the Chi squared statistic of the Homer-Lemslow Goodness of Fit (GOF) test is greater than 10% (or 0.100) in all cases. This suggests that the new and old models adequately fit the data. Third, there is a slight increase in pseudo R squares and area under the ROC curve when industry dummies are added to the model. This suggests that the inclusion of industry dummies potentially improves the explanatory power of the model. Fourth, there is no evidence that cleaning-up the model by excluding the variables which are insignificant in the regression analysis (section 5.2 and 5.3) improves the model's explanatory power. For example, the area under the ROC curve falls from 64.2% in model 15C (full new model) to 61.4% in model 15E (clean new model) and 63.6% in model 15G (restricted new model).

These issues are explored in greater depth in sections 6.2.2 to 6.2.5 below using ROC curve analysis – comparing area under the ROC curve using the Hanley and McNeil (1982) and Delong et al. (1988) methodologies. It is worth noting that the results discussed here do not change when a balanced panel is employed. A summary of the results for area under the Receiver Operating Characteristic curve (AUC) is shown in table 6.2.1b.

Squared distribution with degrees of freedom Df2-Df1. The implication is that, the higher the difference between the -2LL of both models, the higher the probability that the difference is statistically significant, as per Chi Square distribution. Engle (1983) shows that -2 log likelihood test is asymptotically equivalent to the Wald test and the Lagrange multiplier test.

Table 6.2.1b: Summary of area under the ROC curve results: Models 15A - 15H

		Sample size	Targets		Non Targets
		14,093	770		13,323
Area under ROC curve statistics					
		AUC	SE	95% CI	
Model 15A:	Old model	0.599***	0.010	0.591	0.607
Model 15B:	Old model (industry Adj.)	0.611***	0.010	0.603	0.619
Model 15C:	New model	0.642***	0.010	0.634	0.650
Model 15D:	New model (Industry Adj.)	0.649***	0.010	0.641	0.657
Model 15E:	New model_Clean	0.641***	0.010	0.633	0.649
Model 15F:	New model_Clean (Industry Adj.)	0.649***	0.010	0.641	0.656
Model 15G:	New model_Restricted	0.636***	0.010	0.628	0.644
Model 15H:	New model_Restricted (Industry Adj.)	0.645***	0.010	0.637	0.653

Notes: The table summarises the area under the ROC curve results for models 15A to 15H. Model 15A represents a logit regression model where the dependent variable is takeover probability and the independent variables are the old prediction hypotheses (old model). Model 15B is similar to model 15A but controls for industry using industry dummies. Model 15C is the new model. It combines the old and new hypotheses. Model 15D is similar to model 15C but controls for industry using industry dummies. Industry classifications are discussd in table 4.2.2. Model 15E is the new model without the new variables which are found to be insignificant (in section 5.3). These variables include Age Squared, MRDummy, SRDummy and ZScore. Model 15E is therefore a clean version of the new model. Model 15F is similar to model 15E but controls for industry differences using industry dummies. Model 15G is a restricted version of the clean new model. It excludes the old hypotheses which are found to be insignificant in the regression analyses in section 5.2 Model 15H replicates 15G but controls for industry using industry dummies. Standard Errors (SE) and 95% Confidence Intervals (95% CI) are computed using the Hanley and McNeil (1982) methodology. The SE results (to 3 decimal places) obtained using the Hanley and McNeil (1982) methodology is equivalent to standard erros computed using the DeLong et al. (1988) methodology. *, ** and *** indicate significance of AUC at the 10%, 5% and 1% levels, respectively.

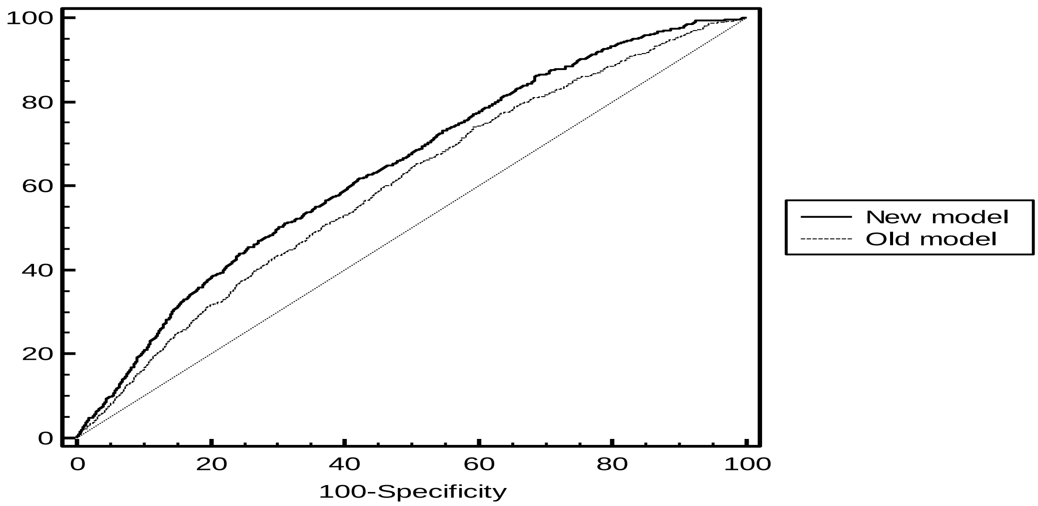
Area under Receiver Operating Characteristic curve (AUC) comparisons are performed in sections 6.2.2 to 6.2.5.

6.2.2 AUC Comparisons: New versus old model

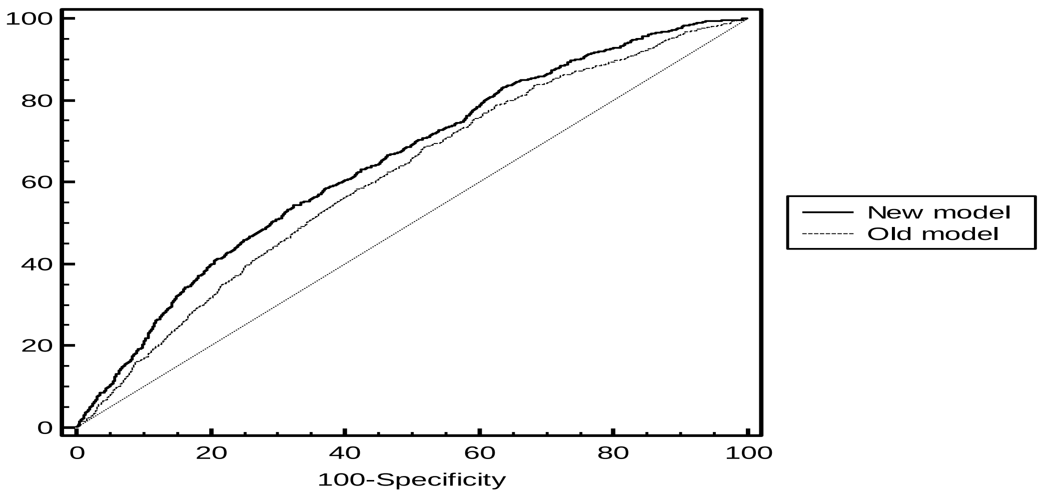
This section compares the AUC results of models 15C and 15D (new models) to those of models 15A and 15B (old models). Models 15C and 15A are unadjusted models while 15D and 15B are industry adjusted models. The ROC curves generated (using the Medcalc software) are presented in table 6.2.2.

Table 6.2.2: AUC Comparisons: New versus old model

Panel A: New versus old model (unadjusted)



Panel B: New versus old model (industry-adjusted)



Panel C: Summary of results

	Panel A	Panel B
AUC: New model	0.642***	0.649***
AUC: Old model	0.599***	0.611***
Difference between areas	0.043***	0.038***
Standard Error of diff (H&M)	0.009	0.008
Z Statistic	4.895	4.551
Significance level (p. value)	<0.0001	<0.0001

Notes: The table shows comparison of areas under the ROC curve (AUC) of the old and new models. The comparison is performed using the Hanley and McNeil (1982) methodology. Panel A pesents ROC curves comparing the performance of the old and new models. Panel B presents results obtained when the old and new models are industry-adjusted. The ROC curves plot sensitivity on the y axis and 100-specificity on the x axis. Panel C presents key statistics for the curves panel A and B. These include the AUC and the statistical significance of the difference in AUC – computed using the Hanley and McNeil (1982) methodology. The analysis are performed in MedCalc. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

As evident in panel A and B, the AUC for the new model (0.642) is greater than that of the old model (0.599). This relationship persists when industry differences are controlled for using industry dummies (panel B). The difference in the AUC (0.043) is significant at the 1% level – based on the Hanley and McNeil (1982) methodology. The results suggest that the new model is clearly an improvement of the old model and is a better fit to the underlying data.

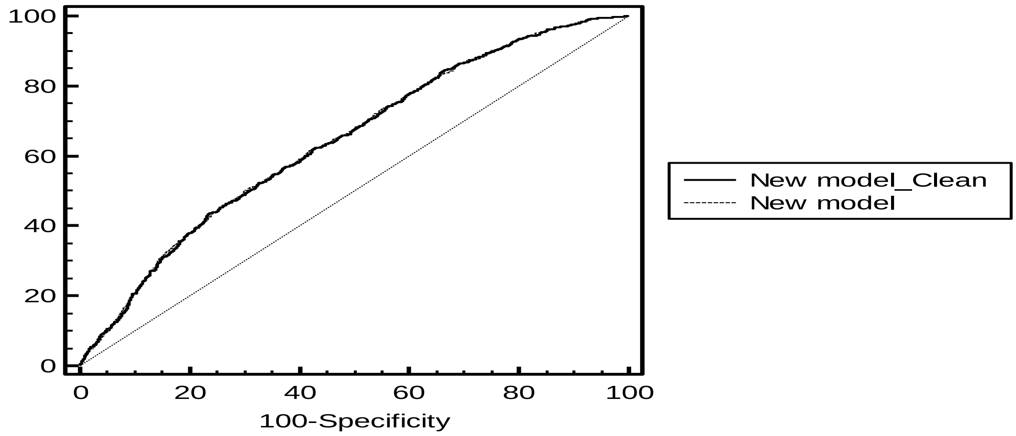
6.2.3 AUC Comparisons: New model (Clean) versus New model (General)

Some of the new variables are found to lack residual explanatory power in the model. For example, I find that the coefficients of MRDummy (a proxy for the merger rumour hypothesis), SRDummy (a proxy for the share repurchase hypothesis), Z Score (one of the proxies for the financial distress hypothesis), and Age square (a proxy for the firm lifecycle hypothesis) were not statistically significant (at the 10% level) in the model. This finding partly questions their relevance in the model. Here, I evaluate whether a cleaner version of the new model (which excludes the variables with statistically insignificant coefficients) outperforms the more general version of the new model. The results from AUC analyses are presented in table 6.2.3.

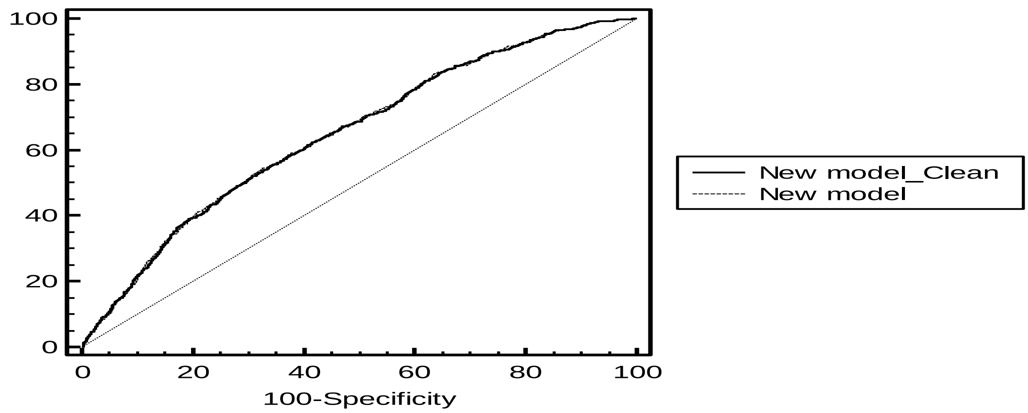
As shown in panel A and B, the AUC for the cleaner version of the new model (0.641) is less than that of the more general version of the new model (0.642). As shown in panel B, the results do not change when industry differences are controlled for using industry dummies. The difference in AUC (0.001) is not significant at the 10% level suggesting that the cleaner version of the new model neither outperforms nor underperforms the more general version. Given that the AUC of the general model is higher than the AUC of the cleaner model, there is no pressing need to exclude these variables (MRDummy, SRDummy, Taffler Z Score and Age Square) from the model. Such an approach can be perceived as a data-mining exercise and deviates from the objectives of chapter 3 – hypothesis development. Nonetheless, these variables appear to add little to the model's explanatory power. In section 6.2.4, I consider a more restricted form of the model.

Table 6.2.3: AUC Comparisons: New model (Clean) versus New model (General)

Panel A: Unadjusted



Panel B: Industry-adjusted



Panel C: Summary of results

	Panel A	Panel B
AUC: New model_Clean	0.641***	0.649***
AUC: New model	0.642***	0.649***
Difference between areas (sig.)	0.001	0.001
Standard Error (H&M)	0.001	0.001
Z Statistic	0.899	0.837
Significance level (p. value)	0.368	0.403

Notes: The table shows comparison of areas under the ROC curve (AUC) of the clean and general new models. The comparison is performed using the Hanley and McNeil (1982) methodology. Panel A pesents ROC curves comparing the performance of the clean and general new models. Panel B presents results obtained when the models are industry-adjusted. The ROC curves plot sensitivity on the y axis and 100-specificity on the x axis. Panel C presents key statistics for the curves panel A and B. These include the AUC and the statistical significance of the difference in AUC – computed using the Hanley and McNeil (1982) methodology. The analysis are performed in MedCalc. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

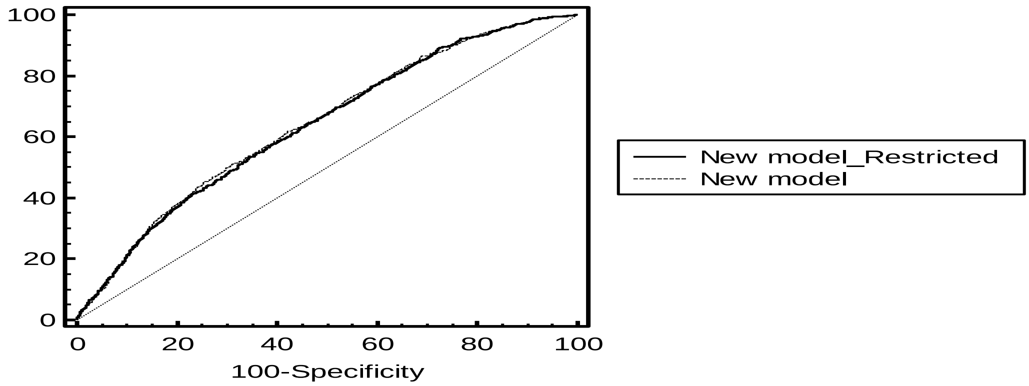
6.2.4 AUC Comparisons: New (restricted) versus new (general) model

Several of the old variables are found to lack residual explanatory power in the model. For example, I find that the coefficients of sales growth, GRDummy (a proxy for the growth-resource mismatch hypothesis), IDummy (a proxy for the industry disturbance hypothesis), NBVDummy (one proxy for the firm undervaluation hypothesis), profitability and LMDummy (proxies for the management inefficiency hypothesis) were not statistically significant (at the 10% level) in the model. This finding partly questions their relevance in the model. I evaluate whether a restricted version of the new model (which excludes the old variables with statistically insignificant coefficients) outperforms the more general version of the new model. The results from area under the ROC analyses are presented in table 6.2.4.

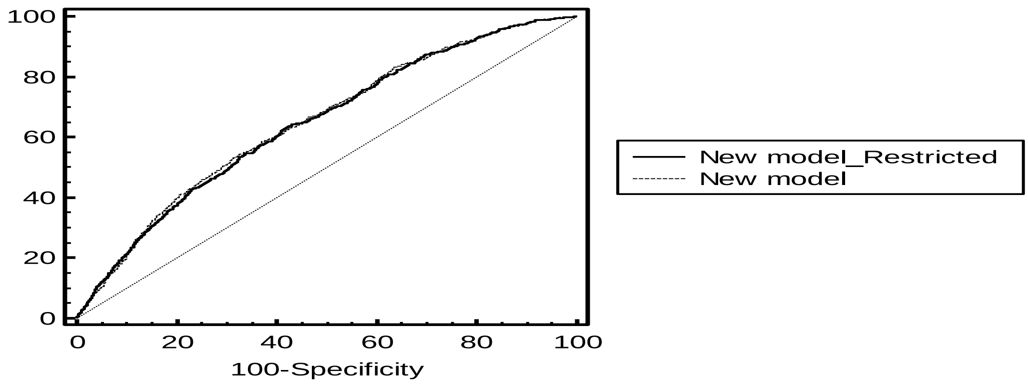
As shown in panel A and B, the AUC for the restricted version of the new model (0.636) is slightly less than that of the more general version of the new model (0.642). The relationship is robust to industry adjustments. The significance of the difference in the AUC (0.004) suggests that the restricted version of the new model underperforms the more general version. The results indicate that despite their lack of statistical significance, these variables (sales growth, GRDummy, IDummy, NBVDummy, profitability and LMDummy) improve the model’s ability to correctly classify takeover targets. These variables should therefore be retained in the model.

Table 6.2.4: AUC Comparisons: New (restricted) versus new (general) model

Panel A: Unadjusted



Panel B: Industry-adjusted



Panel C: Summary of results

	Panel A	Panel B
AUC: New model_Restricted	0.636***	0.645***
AUC: New model	0.642***	0.649***
Difference between areas	0.004*	0.004*
Standard Error (H&M)	0.003	0.003
Z Statistic	1.711	1.697
Significance level (p. value)	0.087	0.090

Notes: The table shows comparison of areas under the ROC curve (AUC) of the restricted and general new models. The comparison is performed using the Hanley and McNeil (1982) methodology. Panel A pesents ROC curves comparing the performance of the clean and general new models. Panel B presents results obtained when the models are industry-adjusted. The ROC curves plot sensitivity on the y axis and 100-specificity on the x axis. Panel C presents key statistics for the curves panel A and B. These include the AUC and the statistical significance of the difference in AUC – computed using the Hanley and McNeil (1982) methodology. The analysis are performed in MedCalc. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

6.2.5 AUC Comparisons: The impact of industry adjustment

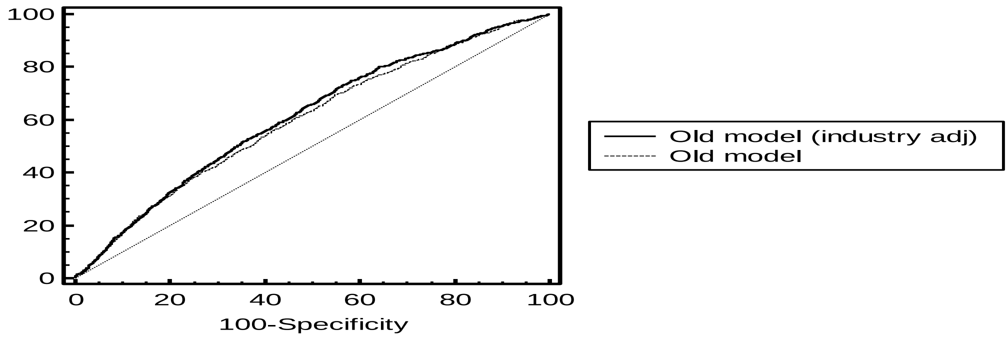
Another issue of concern is the relevance of including industry dummies in the model, i.e., whether the inclusion of industry dummies improves the model's performance. The initial results in table 6.2.1a suggest that industry dummies improve model performance. For example, as can be seen from table 6.2.1a, the Cox and Snell and Nagelkerke R squares increases by about 0.001 and 0.004, respectively, when industry dummies are included in the model. The area under the ROC curve can be further used to compare the models directly.

As shown in panel A and B (table 6.2.5), the area under ROC curve for the unadjusted version of the old model (0.599) is slightly less than that of the industry-adjusted version of the model (0.611). The difference in area under the ROC curve (0.011) is significant at the 1% level. Similarly, the area under ROC curve for the unadjusted version of the new model (0.642) is slightly less than that of the industry-adjusted version of the model (0.649). The difference in area under the ROC curve (0.008) is significant at the 5% level. The results indicate that the unadjusted version of the models underperforms the industry-adjusted versions. The results suggest that industry-adjustment (using industry dummies), perhaps, improve the models' performance.

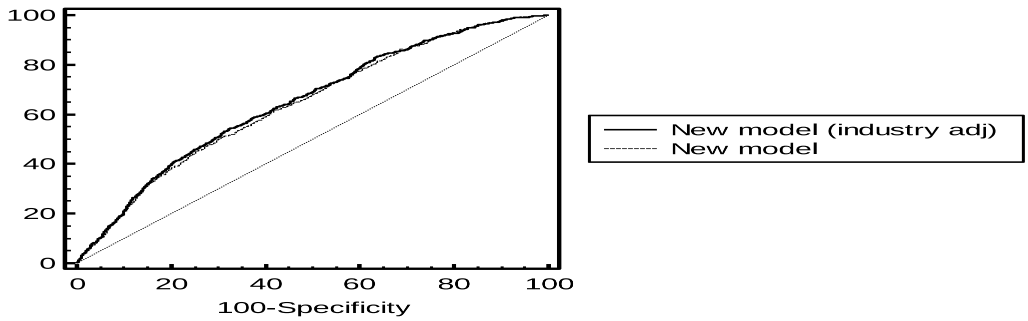
In summary, the results from section 6.2 suggest that the new model performs better than the old model when the AUC is considered. A general version of the model (with all new variables) performs at least as good as a more restricted version (with only the significant variables). Finally, industry adjustment improves the performance of the model.

Table 6.2.5: AUC Comparisons: The impact of industry adjustment

Panel A: Old model



Panel B: New model



Panel C: Summary of results

	Panel A (old Model)	Panel B (new model)
AUC: Industry adjusted model	0.611***	0.649***
AUC: Unadjusted model	0.599***	0.642***
Difference between areas	0.011***	0.008**
Standard Error (H&M)	0.004	0.003
Z Statistic	2.631	2.245
Significance level (p. value)	0.009	0.025

Notes: The table shows comparison of areas under the ROC curve of the unadjusted and industry-adjusted models. The comparison is performed using the Hanley and McNeil (1982) methodology. Panel A pesents ROC curves comparing the performance of the clean and general new models. Panel B presents results obtained when the models are industry-adjusted. The ROC curves plot sensitivity on the y axis and 100-specificity on the x axis. Panel C presents key statistics for the curves panel A and B. These include the area under the ROC curve (AUC) and the statistical significance of the difference in AUC – computed using the Hanley and McNeil (1982) methodology. The analysis are performed in MedCalc. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

6.3 Out-of-sample predictive ability

Arguably, the best performance indicator for a predictive model is how well the model is able to predict the event out-of-sample (see, for example, Inoue and Kilian (2005)). Out-of-sample testing has, increasingly, become the accepted method for validating prediction models in finance research[169]. The focus of this section is therefore to evaluate the new takeover prediction model's ability to predict takeover targets in out-of-sample analyses. The old model is used as a benchmark in this analysis. A balanced panel dataset was not applied in this study as it would have led to a substantial loss of data (discussed in section 4.4.2). The effect of using an unbalanced panel dataset is that the old model employs a larger sample (when compared to the new model) as it is less restrictive in its data requirements. This is further discussed in section 4.4.2. It is uncertain whether this larger sample accords an advantage or a disadvantage to the old model when it is directly compared with the new model. To eliminate potential bias in the comparison between the old and new model, the old model is redeveloped using a balanced panel – the exact dataset used by the new model. The results from this further robustness check are described as the 'old (balanced) model'.

As discussed in section 4.4.4, the parameters of the new and old models are generated using data in period *t* and these parameters are used to compute takeover probabilities (out-of-sample) in period *t+1*. A cross-section of portfolio selection criteria including deciles, quintiles, percentiles and fixed portfolios are applied[170]. For simplicity, I consider these different selection criteria (portfolios types) as independently being used by different model users (or investors). Assuming equal weighting, the overall performance of the model can therefore be considered as the average performance across this portfolio selection criteria. This approach to portfolio selection is applied in each out-of-sample test and the total number of predicted targets as well as the number of actual targets over the portfolio holding period (with annual rebalancing) is computed. The portfolio concentration (which measures the model's performance) is given by the ratio of actual number of targets in the portfolio to the total number of predicted targets from the selection criteria.

[169] See, for example, Campbell and Thompson (2008), Welch and Goyal (2008), Pesaran and Timmermann (2002), Chava and Jarrow (2004), Shumway (2001), Palepu (1986), Barnes (1999), Walter (1994) and Powell (2001), amongst others.

[170] In section 6.9, I further investigate which of these selection criteria is optimal for target prediction.

Table 6.3.1: Out-of-sample predictive ability of the new, old and old (balanced) models

Panel A: New model versus old model

	New Model			Old Model			Diff in Conc. (%)	
	Pred.	Targets	Conc. (%)	Pred.	Targets	Conc. (%)	Diff. (pp)	p. value
D10	1,490	156	10.47	1,852	155	8.37	2.10**	0.0136
Q5	2,973	296	9.96	3,696	293	7.93	2.03***	0.0030
Port100	1,500	156	10.40	1,500	122	8.13	2.27**	0.0118
Port50	750	84	11.20	750	61	8.13	3.07***	0.0015
Port30	450	49	10.89	450	40	8.89	2.00	0.1558
Port10	150	14	9.33	150	12	8.00	1.33	0.6976
Cut off	2,450	199	8.12	1,535	141	9.19	-1.06	0.8862
Port5%	748	84	11.23	930	73	7.85	3.38***	0.0046
Overall	**10,511**	**1,038**	**9.88**	**10,863**	**897**	**8.26**	**1.62*** **	**0.0002**
Sample	**14,833**	**1,029**	**6.94**	**18,440**	**1,261**	**6.84**	**0.10**	**0.5051**

Panel B: New model versus old model (balanced)

	New Model			Old (Balanced) Model			Diff in Conc.	
	Pred.	Targets	Conc.	Pred.	Targets	Conc.	Diff. (pp)	p. value
D10	1,490	156	10.47	1,490	129	8.65	1.82**	0.0189
Q5	2,973	296	9.96	2,973	231	7.77	2.18***	0.0004
Port100	1,500	156	10.40	1,500	127	8.47	1.93**	0.0137
Port50	750	84	11.20	750	67	8.93	2.27***	0.0046
Port30	450	49	10.89	450	40	8.89	2.00**	0.0450
Port10	150	14	9.33	150	14	9.33	0.00	1.0000
Cut off	2,450	199	8.12	2,450	213	8.68	-0.56	0.4919
Port5%	748	84	11.23	748	68	9.12	2.11**	0.0238
Overall	**10,511**	**1,038**	**9.88**	**10,511**	**889**	**8.46**	**1.42*** **	**0.0005**
Sample	**14,833**	**1,029**	**6.94**	**14,833**	**1,029**	**6.94**	**0.00**	**1.0000**

Notes: The table presents summary results from out-of-sample predictions of the new, old and old (balanced) models. Panel A compares the performance of the new model with that of the old model. Panel B compares the performance of the new model with that of the old (balanced) model. The old and new models use all the variables in model 15A and 15C (table 6.2.1a), respectively. The models are developed in a recursive manner and used to predict targets one-year ahead. The first parameters are developed using data from 1989 to 1994. These parameters are used to make predictions (compute takeover probabilities for firms) in 1995. The model is then redeveloped again using data fom 1989 to 1995 for use in prediction in 1996. This process is continued until 2009 where data for the period 1989 to 2008 is used to develop parameters for prediction in 2009. Firms are ranked by their (predicted) takeover likelihood and firms with the highest takeover likelihood are selected as potential targets. Different criteria (Port100, Port50, Port30, Port10, D10, Q5 and Cut off) are used to determine what number of potential targets to select. Port100, Port50, Port30, and Port10 are portfolios of 100, 50, 30 and 10 firms with the highest probability of receiving the bids. D10 and Q5 are the 'top' decile and quintile portfolios respectively. Pred. is the number of predicted targets. Targets is the number of actual targets within Pred. Conc.% is the ratio (%) of Target to Pred. t-test for paired samples is used to compare the target concentrations achieved by the different models over the 15-year out of sample period spanning 1995 to 2009. 'Overall' represents the 'average' performance of each model. 'Sample' represents the performance of a model which simply predicts that every firm in the population is a takeover target. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 6.3.1 presents summary results on the performance of the recursive models over a 15 year period. Panel A compares the performance of the new model with that of the old model. Panel B compares the performance of the new model with that of the old (balanced) model. The old and new models use all the variables in model 15A and 15C (table 6.2.1a), respectively. The models are developed in a recursive manner and used to predict targets one-year ahead. The first parameters are developed using data from 1989 to 1994. These parameters are used to make predictions (compute takeover probabilities for firms) in 1995. The model is then redeveloped again using data from 1989 to 1995 for use in prediction in 1996. This process is continued until 2009 where data for the period 1989 to 2008 is used to develop parameters for prediction in 2009. Firms are ranked by their (predicted) takeover likelihood and firms with the highest takeover likelihood are selected as potential targets. Different criteria (Port100, Port50, Port30, Port10, D10, Q5 and Cut off) are used to determine what number of potential targets to select. Port100, Port50, Port30, and Port10 are portfolios of 100, 50, 30 and 10 firms with the highest probability of receiving the bids. D10 and Q5 are the 'top' decile and quintile portfolios respectively. Pred. is the number of predicted targets. Targets is the number of actual targets within Pred. Conc.% is the ratio (%) of Target to Pred. *t*-test for paired samples is used to compare the target concentrations achieved by the different models over the 15-year out of sample period spanning 1995 to 2009.

With the exception of the Cut-off probability selection criteria, the new model appears to outperform the old model (and the old (balanced) model) in terms of its ability to predict targets in out-of-sample analysis. The model achieves an overall performance (target concentration) of 9.88%, by correctly predicting 1,038 actual targets out of a total of 10,511 predictions. The old model achieves a significantly lower (at the 1% level) target concentration of 8.26%, by correctly predicting 897 actual targets out of a total of 10,863 predictions. The old (balanced) model which uses exactly the same dataset as the new model is only able to correctly predict 889 actual targets (out of 10,511 predictions). The results also show that the new model outperforms the old and old (balanced) models across most of the different portfolios selection criteria.

Overall, the results provides evidence that the new model has a superior out-of-sample predictive ability (i.e., the ability to correctly identify targets out-of-sample) when compared to the old model. The results are robust to the methodology applied in selecting target portfolios (e.g., D10, Q5, Port100, Port50, Port30, Port10 and Port5%)[171]. The results remain robust when the sample differences between the old and new model are accounted for – as in the old (balanced) model. The out-of-sample performance results are given further context by comparing them against the results in prior studies (in section 6.4).

6.4 Classification and predictive ability – old model versus prior UK studies

Sections 6.2 and 6.3 established that the new model is, on average, better than the old model both in terms of its classification ability (within-sample) and its predictive ability (out-of-sample). This section aims to provide some context to these results by comparing them against the results published in prior UK takeover prediction studies, mainly Powell (2001, 2004). Sample restrictions[172] in this study do not allow for a direct comparison between the results obtained here and those reported in Barnes (1998, 1999, 2000) and Powell (1997). Powell (2001) builds on Powell (1997), using a UK dataset between 1986 and 1995 to develop his model, which is tested on the population of UK firms listed in January 1996. The pooled sample of firms between 1986 and 1995 is made up of 9,891 firm-year observations of which 471 observations are targets.

In line with Barnes (1990, 1998, 1999, 2000), Powell (2001) employs a matched-sample methodology, matching the 471 targets to a selected sample of 471 non-targets[173]. The model is also applied out-of-sample using data (1,000 observations with 29 targets) from 1996. The model achieves a target concentration of 2.44% (based on deciles). Using data from 1988 to 1995 (9,917 firm-year observations of which 330 observations are targets), the old model developed in this study achieves a much higher target concentration of 14.04% in 1996 (based on deciles). The difference between the results reported in this

171 Besides being a robustness test, the consistency in performance across different portfolios indicates that the new model, generally, ascribes higher takeover probabilities to targets than non-targets across the entire sample distribution, as compared to the old model.

172 The new model does not have sufficient observations to derive robust model coefficients using data from 1988 to 1993. The first out-of-sample predictions are made in 1995. Barnes (1998, 1999, 2000) employs a UK sample of firms between 1991 and 1994. The estimation sample in these studies consists of listed firms between 1991 and 1993. Barnes (1999), for example, employs five hypotheses for prediction including inefficient management, firm size, growth-resource mismatch, firm undervaluation and inefficient financial structure (leverage). The model developed from this sample is tested on data from 1994.

173 The estimation sample obtained when outliers are eliminated is made up of 444 targets and 422 non-targets – a final sample of 866 observations.

study and those reported in Powell (2001) can, perhaps, be attributed to the differences in the sampling methodology between the two studies[174]. The new model outperforms both models (Powell (2001) and old model) by achieving a target concentration of 20.59% in 1996 (based on deciles).

The key difference between Powell (2001) and Powell (2004) is that Powell (2004) employs a pooled population (as opposed to a matched-sample used in Powell (2001)). This pooled population sampling methodology is similar to the sampling technique employed in this study. The exact dataset used in Powell (2001) is applied in Powell (2004). This dataset consists of 9,037 UK firm-year observations with 447 targets between 1986 and 1995. Data from 1996 (holdout sample) consisting of 1,000 observations of which 29 are targets is used to test his models. Powell's model B achieves a target concentration of 4.72% in 1996 (using cut-off probabilities) and an overall predictive ability of 93.3%. This result shows an improvement of 14.85pp (percentage points) from the 78.45% overall predictive ability reported in Powell (2001). The difference can directly be attributed to a change in the sampling methodology (from matched-samples to pooled population sampling). While there is an improvement in classification ability, Powell's (2004) model achieves less than 3% target concentration across all selection criteria, hence, underperforming both the old and new models in this study. In the 1996 holdout sample, the old model in this study achieves a higher target concentration of 12.75% using cut-off probabilities computed using Powell's methodology (developed in Powell (2001)).

Sections 6.2 to 6.4 focus on ascertaining the superior performance of the new model. The results in these sections suggest that the new model (as well as the modelling methodology employed in this study) is indeed an improvement on previous models. In sections 6.5 to 6.8, the focus shifts from comparing the models' performances to evaluating the impact of some methodological choices applied in this study as well as in prior literature on the reported results. Section 6.5 explores how the performance of the models changes over time – stability of model performance. Section 6.6 empirically investigates the impact of the length of the estimation period on model performance. It answers the question 'should more data or less data be used in the development of model parameters?' Section 6.7 investigates the usefulness of 'stale' model parameters. It explores whether other researchers and practitioners can use the parameters developed in this study for prediction

[174] Powell (2001) employs a matched-sample approach (as opposed to the pooled population approach employed in this study) and excludes the firm age hypothesis in his model.

in the future. Section 6.8 explores the performance of different portfolio selection criteria with the goal of identifying the best selection criteria in this context.

6.5 The (in)–stability of model predictive ability – A critique of prior studies

6.5.1 Overview

In this study, the models are recurrently redeveloped using new data and are tested (and retested) over several holdout periods (1995–2009). The reported performance of the models (see section 6.4) is the long run (1995–2009) average across different selection criteria (deciles, quintiles, percentiles, fixed portfolios and cut-offs) as discussed in section 6.4. The results (reported in section 6.4) suggest that the new model outperforms the old model, on average, irrespective of the time periods considered and the portfolio selection techniques employed.

Several prior studies develop takeover prediction models over an estimation sample of several years but test the model performance over a limited holdout period of one year (see table 6.5.1 for a summary). This issue has been discussed in section 2.5 and section 2.6 where it was argued (in section 2.6) that such an approach of evaluating performance (based on one year of out-of-sample data), potentially, results in biased, unreliable or non-generalisable conclusions.

A majority of prior studies evaluate their model out-of-sample performance over a period of one year (e.g., Palepu (1986), Walter (1994), Barnes (1998, 1999, 2000) and Powell (2001, 2004)). Some studies (such as Ambrose and Megginson (1992), Barnes (1990), Powell (2007) and Brar et al. (2009)) do not conduct any out-of-sample tests. To my knowledge, only Cremers et al. (2009) adopts a robust out-of-sample testing framework. Nonetheless, Cremers et al. (2009) only evaluate their model's potential to generate abnormal returns and not its ability to correctly predict actual targets in the out-of-sample period. This section illustrates how the use of a one year out-of-sample test period can lead to biased, non-robust and non-generalisable conclusions. This is achieved by highlighting the variations in model predictive ability from one year to another (section 6.5.2) and the impact of bull market and bear market periods (i.e., overall market growth and overall market decline, respectively) on model performance (section 6.5.3).

Table 6.5.1: A summary of the estimation samples and holdout samples used in prior studies.

Study	Estimation period	Prediction period
Palepu (1986)	1971–1979	1980
Ambrose and Megginson (1992)	1981–1986	None
Walter (1994)	1981–1984	1985
Barnes (1990)	1986–1987	None
Barnes (1998, 1999, 2000)	1991–1993	1994
Powell (1997)	1984–1991	None
Powell (2001, 2004)	1986–1995	1996
Brar et al. (2009)	1992–2003	1992–2003
Cremers et al. (2009)	1981–1991 (Recursive)	1992–2004

Notes: The studies in this table focus on predicting takeover targets and generating abnormal returns from such predictions. The studies not included in this table focus on other issues such as methodologies for takeover prediction (e.g., Espahbodi and Espahbodi (2003)). The estimation period is the period used to derive model parameters. The prediction period is the period over which the model is validated, either by its ability to identify actual targets or its ability to generate abnormal returns for investors.

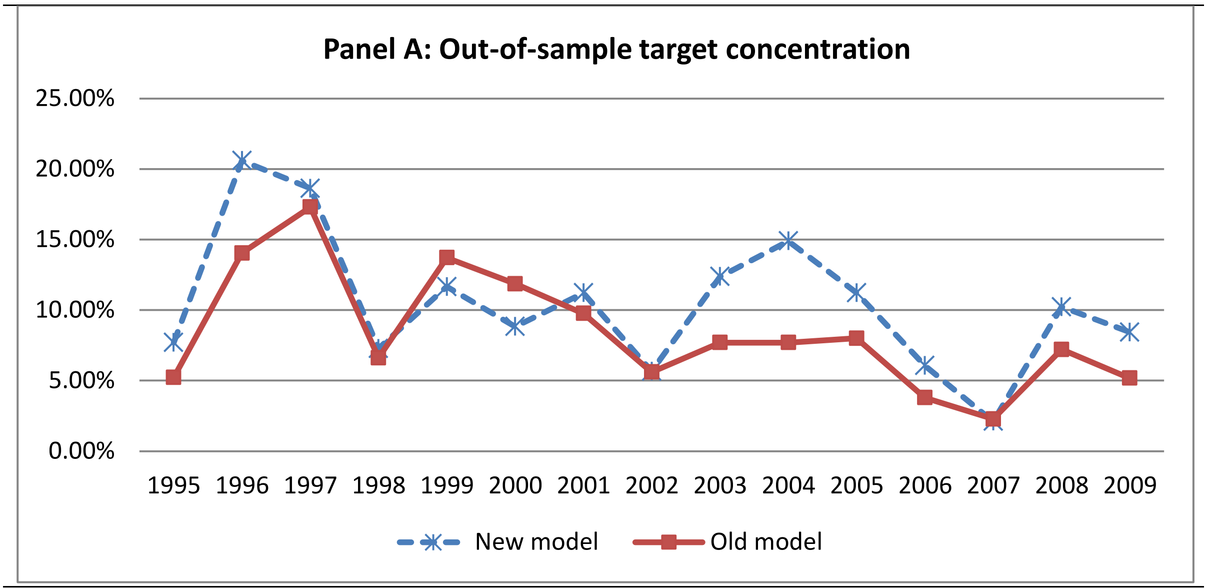
6.5.2 Variations in model predictive ability

Variations in model predictive ability are highlighted by reviewing the models' performances in out-of-sample tests from one year to another. The target concentrations achieved (using the decile selection criteria) by the new and old models in out-of-sample tests between 1995 and 2009 are reported in figure 6.5.2[175].

The out-of-sample performance of the models (i.e., percentage of correct prediction) significantly changes from one period to another. For example, the new model attains a target concentration of 20.59% in 1996 and 2.11% in 2007. Similarly, the old recursive model also attains a target concentration of 17.29% in 1997 and 5.60% in 2002. The standard deviation (representing the average distance from mean target concentration) is over 4.87% for the new model and 4.19% for the old model.

[175] The results achieved using other estimation periods (five-year and ten-year) and other selection criteria (quintiles, percentiles, and fixed portfolios) are consistent with these results.

Figure 6.5.2: Variations in model predictive ability between 1995 and 2009



Panel B: Summary descriptive statistics

	New model	Old model
Mean	10.46%	8.39%
Median	10.23%	7.69%
Standard Devn	4.87%	4.19%
Kurtosis	0.40	-0.07
Skewness	0.60	0.74
Minimum	2.11%	2.27%
Maximum	20.59%	17.29%
Count	15	15

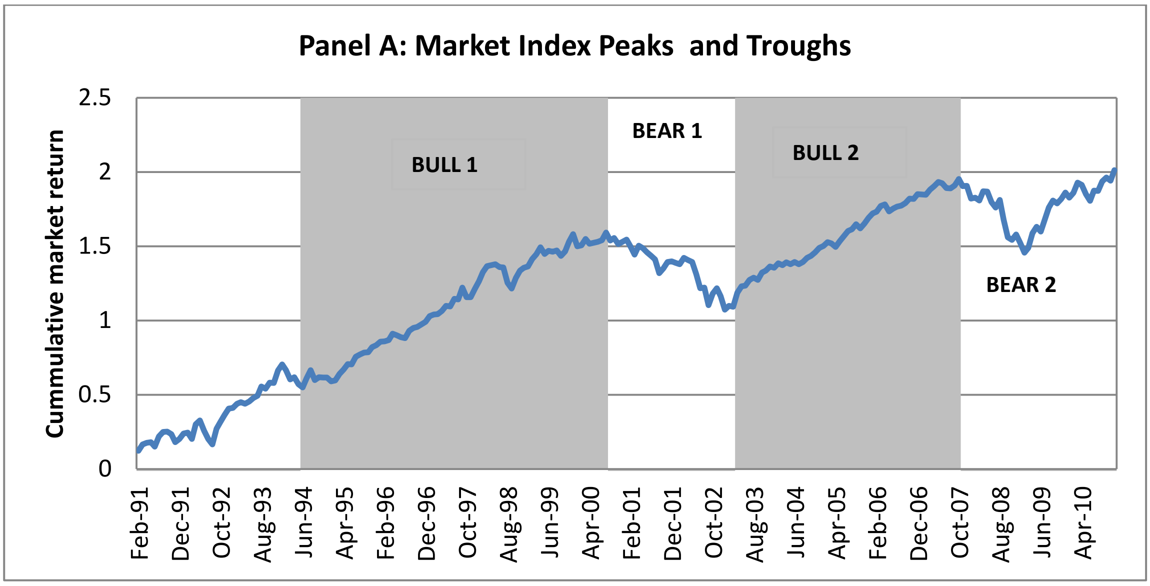
Notes: The figure shows the variations in model predictive ability (out-of-sample) from one year to another. Deciles are used as the selection criteria. A similar conclusion is reached when other portfolio selection criteria are applied. Panel A shows a graph that plots target concentration of the Y axis against year on the X axis. The analysis covers the 15-year period from 1995 to 2009. These results are achieved through recursive predictions. The first model parameters are developed using data from 1989 to 1994. These parameters are used to make predictions (compute takeover probabilities for firms) in 1995. The model is then redeveloped again using data fom 1989 to 1995 for use in prediction in 1996. This process is continued until 2009 where data for the period 1989 to 2008 is used to develop parameters for prediction in 2009. Firms are ranked by their (predicted) takeover likelihood and the 10% (decile) of firms with the highest takeover likelihood are selected as potential targets. Panel B shows descriptive statistics of the target concentration results.

The substantial range in out-of-sample performance (18.48% and 15.02% for the new and old models, respectively) highlights the bias involved in testing a target prediction model over a single year. For example, using only data from 2007 to test the models yields a conclusion that the model achieves low target concentrations of 2.11% (new model) and 2.27% (old model). This conclusion is clearly misleading. The results therefore suggest that, for robustness, out-of-sample testing should be carried out over a long time period as has been done in the current study.

6.5.3 Variations across bull and bear market periods

In this section, I further illustrate that out-of-sample performance is generally higher if the out-of-sample test period corresponds to a period of market growth (bull period) as compared to a period of market decline (bear market period). To achieve this, the performance (cumulative annual returns) of the FTSE all-share index is compared against the top decile target concentrations achieved by the new and old models (see figure 6.5.3b). Figure 6.5.3a plots the cumulative return on the FTSE All-Share index from 1991 to 2010.

Figure 6.5.3a: Identification of bull and bear markets using cumulative market returns



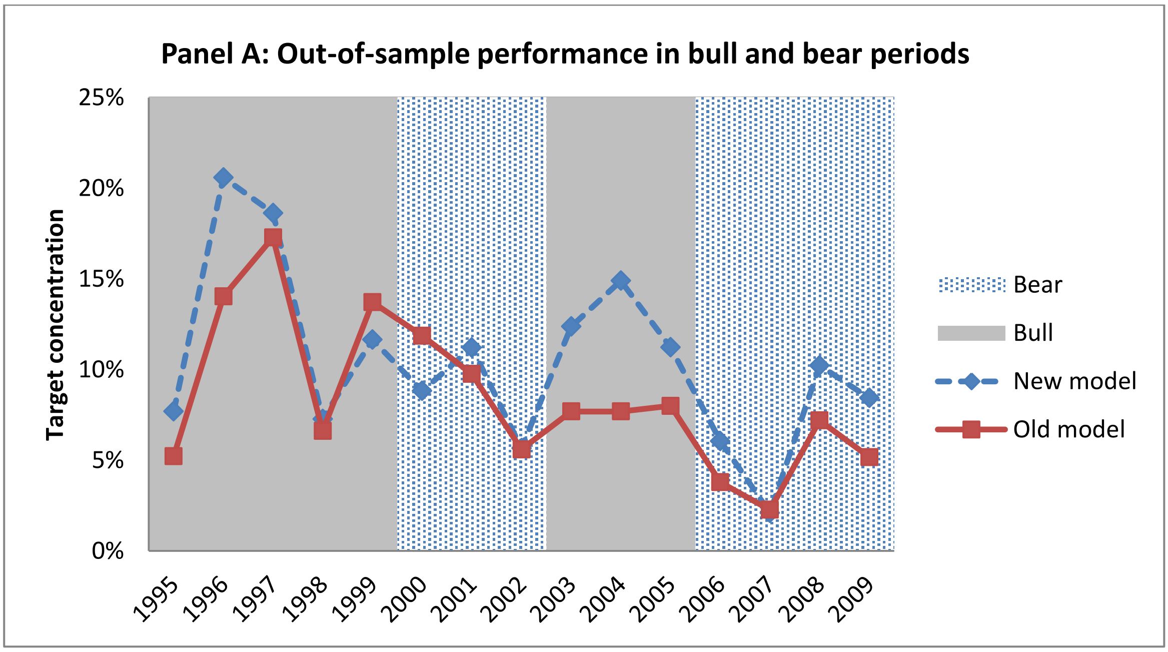
Panel B: Bull and bear periods

PERIOD	CLASSIFICATION
June 1994 – August 2000	BULL 1
September 2000 – March 2003	BEAR 1
April 2003 – October 2007	BULL 2
November 2007 – End	BEAR 2

Notes: The graph plots the cumulative return on the FTSEALL-SHARE index (y-axis) against time (x-axis). The base period for the computation of cumulative returns is January 1991. The goal is to visually identify peaks and troughs in the index. The period between a trough (positive-turning point) and a peak (negative-turning point) is considered as a BULL market period – indicating a period of market growth, and vice versa. The first Bull period is identified as June 1994 and this is used as the start period for the analysis. BULL 1 and BULL 2 refer to the periods of market growth while BEAR 1 and BEAR 2 refer to the periods of market decline. For simplicity secondary trends are not considered.

Given the benefit of hindsight, one can approximate the start and end of bull and bear periods by using cumulative market (FTSE All-Share index) returns over time. From figure 6.5.3a, two major periods of market decline are evident: post–2000 and post–2007. These periods, perhaps, coincide with the dotcom crisis and the global financial crisis periods. Ignoring short term or secondary trends, and considering the size of the change in cumulative market return, I identify two major bull periods (BULL 1 and BULL 2) and two major bear periods (BEAR 1 and BEAR 2). BULL 1 is considered as the period between June 1994 and August 2000. This bull period (BULL 1) is followed by a bear period (BEAR 1) which runs from September 2000 to March 2003. BEAR 1 is followed by a bull period which runs from April 2003 to October 2007. The period post October 2007 (October 2007 to June 2010) has been considered as a Bear Period for the purpose of this study[176].

Figure 6.5.3b: Cumulative returns on the FTSE All-Share index and variations in (old and new) model predictive ability



Panel B: Differences in performance (mean target concentration)

	New model	Old model
Bull period	13.04%	10.03%
Bear period	7.50%	6.52%
Difference	5.54%	3.51%
P. value	0.01978	0.1016

Notes: The graph in panel A plots the target concentration achieved by the old and new model between 1995 and 2009. This is presented against the backdrop of the cumulative return on the FTSEALL-SHARE index where 'Bull' represents periods of market growth and 'bear' represents periods of market decline. The base period for the computation of cumulative returns is January 1991. Further details about the selection of bull and bear periods are presented in table 6.5.3a. The

[176] It is assumed that (by June 2010) financial markets have not experienced a full recovery since the global financial crisis due to the uncertainty created by the European Debt (Bond Market) crisis. Further, if this post 2007 period is broken down to reflect the fact that the market experienced some growth post 2009, the period for analysis will be too short to allow for any robust analysis.

graph attempts to visually capture the variations in model performance with market performance. The graph shows that the performance of the models (particularly the new model) increases in bull periods and declines in bear periods. Panel B presents a summary of the results obtained in each period. The table shows a tendency for model performance to be better in bull periods.

The model's performance tends to vary substantially with the market (FTSE all-share index) performance as takeover activity generally increases in bull periods and declines in bear periods (Harford (2005)). As shown in figure 6.5.3b, the models report better target concentration ratios in bull periods when compared to bear periods. The results reported in panel B show that this is especially the case for the new model. It achieves an overall target concentration of 13.04% in the bull periods (BULL 1 and BULL 2) as against 7.5% in the bear period (BEAR 1 and BEAR 2). The difference in target concentration is significant at the 5% level.

Overall, the results suggest a tendency for the models to perform better in bull market periods and worse in bear periods. These bull periods (as discussed in Harford (2005)) generally see higher takeover activity. Presumably, firms with target characteristics are more likely to be acquired during these bull periods (than in periods of market decline) as managers have a stronger incentive to engage in acquisitions during periods of market growth (Harford (2005)). The main implication of these results is that studies which employ one year out-of-sample tests are likely to report positively biased results if the test period corresponds to a year with overall market growth, and vice versa. This might partly account for the fact that Barnes (1998, 1999, 2000) reports zero target concentrations in 1994 and Powell (2001, 2004) reports moderate (3.24%) target concentrations in 1996.

6.6 The length of the estimation period in target prediction models

Prior empirical research has raised questions on the choice of estimation samples in model development. Pesaran and Timmerman (2002, 2007) highlight the problem of structural breaks in data and how such breaks can negatively impact on the forecasting ability of regression-based models. Pesaran and Timmerman (2002) propose a two stage process in prediction model development which starts with the identification of structural breaks in data series. The second stage in the process involves the use of post-break data (Pesaran and Timmerman (2007)) or pre-break data (Pesaran and Timmerman (2002)) to develop the model parameters. While such guidance is theoretically sound, the identification of breaks in some datasets presents a significant empirical challenge (also noted in Pesaran and Timmerman (2002, 2007)). In section 5.4, I discussed the changing characteristics of takeover targets over time (1994-2007). A key observation from table 5.4.1 is that no single year can be neatly identified as a structural break in the characteristics of takeover targets. The tests conducted in table 5.4.1 are, in principle, analogous to the Chow test (Chow (1960)) and follow the suggestions of Thomas (1997).

Table 6.6.1: Comparison of the performance of the three-year and recursive models

Panel A: Recursive versus three-year new model

	Recursive new model			Three-year new model			Difference in Conc.	
	Number	Targets	Conc. %	Number	Targets	Conc. %	Diff. (pp)	p. value
D10	1,490	156	10.47	1,490	158	10.60	-0.13	0.9056
Q5	2,973	296	9.96	2,973	308	10.36	-0.40	0.6061
Port100	1,500	156	10.40	1,500	159	10.60	-0.20	0.8538
Port50	750	84	11.20	750	81	10.80	0.40	0.8003
Port30	450	49	10.89	450	57	12.67	-1.78	0.3263
Port10	150	14	9.33	150	22	14.67	-5.33*	0.0878
Port5%	748	84	11.23	748	82	10.96	0.27	0.9510
Overall	8,061	839	10.41	8,061	867	10.76	-0.35	0.1100

Panel B: Recursive versus three-year old model

	Recursive old model			Three-year old model			Difference in Conc.	
	Number	Targets	Conc. %	Number	Targets	Conc. %	Diff. (pp)	p. value
D10	1,852	155	8.37	1,852	179	9.67	-1.30	0.1031
Q5	3,696	293	7.93	3,696	368	9.96	-2.03**	0.0134
Port100	1,500	122	8.13	1,500	155	10.33	-2.20**	0.0163
Port50	750	61	8.13	750	73	9.73	-1.60	0.2711
Port30	450	40	8.89	450	40	8.89	0.00	1.0000
Port10	150	12	8.00	150	16	10.67	-2.67	0.1038
Port5%	930	73	7.85	930	95	10.22	-2.37*	0.0952
Overall	9,328	756	8.10	9,328	926	9.93	-1.82***	0.0001

Notes: The table presents summary results from out-of-sample predictions of the recursive and three-year new and old models. Panel A compares the performance of the recursive new model with that of the three-year new model. Panel B compares the performance of the recursive old model with that of the three-year old model. The old and new (recursive and three-year) models use all the variables in model 15A and 15C (table 6.2.1a), respectively. The recursive models have a base year of 1988 and use all data available prior to the year of prediction. The three-year model use three years of data up to the year prior to the year of predictions. The first predictions are made in 1995. The models are then redeveloped again to include data for 1995 for use in prediction in 1996. This process is continued until 2009 where data for the period 1989 to 2008 (2006 to 2008) is used to develop parameters of the recursive (and three-year) model for prediction in 2009. Firms are ranked by their (predicted) takeover likelihood and firms with the highest takeover likelihood are selected as potential targets. Different criteria (Port100, Port50, Port30, Port10, D10, Q5 and Cut off) are used to determine what number of potential targets to select. Port100, Port50, Port30, and Port10 are portfolios of 100, 50, 30 and 10 firms with the highest probability of receiving the bids. D10 and Q5 are the 'top' decile and quintile portfolios respectively. Pred. is the number of predicted targets. Targets is the number of actual targets within Pred. Conc.% is the ratio (%) of Target to Pred. t-test for paired samples is used to compare the target concentrations achieved by the different models over the 15-year out of sample period spanning 1995 to 2009. 'Overall' represents the 'average' performance of each model. 'Sample' represents the performance of a model which simply predicts that every firm in the population is a takeover target. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

In this section, the impact of the length of the estimation window is evaluated by comparing the performance of a model which uses a three-year window to estimate model parameters (three-year rolling model)[177] against the performance of a model which uses all the data available (a recursive model). For example, to predict targets in 2000, the three-year recursive model uses data from 1997 to 1999 to develop model parameters while the recursive model uses data from 1988 to 1999. Again, to predict targets in 2001, the three-year rolling model uses data from 1998 to 2000 while the recursive model uses data from 1988 to 2000[178]. The first predictions are made in 1995, and then predictions are made every year until 2009. The results obtained over the 15-year period (1995–2009) using both the old and the new models are reported in table 6.6.1.

The results from table 6.6.1 show that between 1995 and 2009, the recursive model (long estimation window) underperforms the three-year model (short estimation windows) on an average basis, for both the old and new model specifications. For the new model, the recursive model achieves an overall target concentration of 10.41% while the three-year model achieves a slightly higher overall target concentration of 10.76%. The difference in target concentration (0.35 pp) is not significant. For the old model, the three-year model achieves a target concentration of 9.93% as against 8.10% achieved by the recursive model. The difference in target concentration (1.82 pp) is significant at the 1% level. The results suggest that shorter estimation windows can be more optimal for the development of takeover prediction models – at least for the old model. Perhaps, the reason for this is the argument that target characteristics change over time (further discussed in section 5.4). This finding is inconsistent with the observation that several studies in takeover prediction employ the longest estimation windows permitted by their data.

Section 6.6 focused on the relevance of the length of the estimation window. The results from section 6.6 broadly indicate that the use of shorter estimation windows is potentially, a more optimal strategy for model development. The next section (section 6.7) considers the issue of stability of model parameters for prediction several years ahead. That is, whether parameters developed today are useful in making predictions several years from today.

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177 Three years is preferred as it is the smallest time period which allows for robust coefficients to be developed. The coefficients obtained when one year and two years are used are insignificant and unstable over time.

178 The base year for estimation used in the recursive model is 1988 while the base year used in the recursive model is continually rolled such that the estimation sample spans over three years.

6.7 Long term stability of model parameters – Stale versus fresh model parameters

6.7.1 Overview

This section seeks to assess the relevance and the stability of current model parameters (e.g., parameters developed using estimation data from 1988-1999) for prediction several years in the future (e.g., 2010-2020). The relevance of this investigation is based on the observation that model coefficients developed in finance research are frequently used by researchers and practitioners several years after their development. An example is the use of Taffler Z score model coefficients and the Altman's Z score model coefficients (developed more than three decades ago – Taffler (1982, 1983, 1984) and Altman (1968)) in contemporary research (see Agarwal and Taffler (2007) and Shumway (2001), amongst others). This study, for example, also uses the original Taffler Z score model parameters to compute each observation's likelihood of bankruptcy or financial distress. The main reason for the use of these presumably 'stale' model parameters is the cost associated with collection and analyses of new data[179]. The evidence (see Agarwal and Taffler (2007)) suggests that parameters might sometimes be robust across time, as in the case of Taffler Z score parameters.

As discussed in section 2.5.6, several new studies (see, for example, Cremers et al. (2009), Bhanot et al. (2010) and Cornett et al. (2011)) employ firm takeover probabilities as one of the independent variables in their empirical research. Cornett et al. (2011), for example, investigate investors' anticipation of bidder and target candidacy in takeovers and whether this anticipation moderates the distribution of wealth between bidders and targets during takeover contests. The researchers (Cornett et al. (2011) start by developing a model to measure takeover risk for each firm in their sample and this measure of risk is then used to develop a surprise instrument (a measure of market anticipation). Given that the main focus of Cornett et al. (2011) is not to measure takeover risk, the study employs a simple model akin to the Palepu (1986) model to measure takeover risk[180]. While the results of

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179 Cram et al. (2009), for example, contends that the choice of methodology (e.g., the use of matched-sample methodology) across several studies in accounting and finance is driven by data collection costs.

180 Cornett et al. (2011) model probability of making a bid (bidder), receiving a bid (target) and not involved in M&A (non-target, non-bidder) as a logit function of sales shock, size, change in size,

these studies (which employ takeover probability as an input variable) is, potentially, moderated by how well the model captures the concept, little consideration is given to developing an optimal model. The new model developed in this study, perhaps, provides a more efficient model for ascribing takeover probabilities. Its application requires the redevelopment of model parameters from 19 hypotheses and 27 input variables. Given the data collection costs that this imposes (especially for future researchers), I consider the use of current model parameters (which might be considered to be stale in the next few years) for prediction of takeover targets or ascribing takeover risk in the future[181].

In this section, I use the phrase 'stale model parameters' to describe model parameters developed from, presumably, old data. I also use the phrase 'fresh model parameters' to describe parameters developed using the data assumed to be available at the point of portfolio development. In the first instance, the out-of-sample performance achieved using stale model parameters is evaluated over a period of ten years (section 6.7.2). Second, I investigate whether the length of the estimation sample (short estimation sample versus long estimation sample) affects the performance of stale models (section 6.7.3). Presumably, longer estimation windows can generate more stable and efficient stale parameters, in line with the findings in section 6.6. Third, the performance achieved using the stale model parameters is directly compared with the performance achieved using fresh model parameters (section 6.7.4). Last, I investigate whether the new model still outperforms the old model when stale model parameters are employed (section 6.7.5).

6.7.2 Performance of stale model parameters over a holdout sample

In this section, the long run variation of the performance of the new model employing stale parameters is evaluated. The results for the three-year and recursive variants of the new model are reported. The coefficients of the recursive variant of the new model are derived from data between 1988 and 1999. These coefficients are used to recurrently predict targets each year between 2000 and 2009 – without coefficient redevelopment. Data from 1994-

industry concentration, growth-resource mismatch, return on assets, cash ratio, price run-up, information asymmetry and participation in previous mergers.

[181] It is unlikely that these tests will be useful for investors (with significant amount of resources). It is, however, likely that this will be useful for researchers (using takeover probability as one of the input variables in their research), management (simply interested in assessing their takeover risk from one year to another), or regulatory/law makers (interested in understanding the changing dynamics of takeover targets from one year to another or the impact of a particular regulation on takeover probability).

1996 is used to develop the coefficients of the three-year variant of the new model[182]. These coefficients are tested out-of-sample over the period from 1997–2009 – without any coefficient redevelopment. The expectation is that if the model's predictive power declines over time, then a systematic decline in model predictive ability should be observed. Figure 6.7.2 reports the performance of the stale new model when applied to out-of-sample data from 1997 to 2009.

The stale three-year model is developed using data from 1994–1996 and tested out-of-sample using data from 1997–2009. The chart in table 6.7.2 (panel B) highlights the variability in the model's performance over the 13 year period across different portfolio selection criteria (D10, Q5 and Port100). Interestingly, the chart shows that the performance of the stale model does not systematically decline from 1997 to 2009 (or from 2000–2009). Using the decile selection criteria, the model achieves target concentration of 18.82 % in 1997 (the year after model development) and a target concentration of 17.33% in 2005 (eight years after model development). This non-decline in the performance of stale model parameters is also confirmed when the performance of the stale recursive model is assessed.

The stale recursive model uses a longer estimation window (1988–1999) compared to the stale three-year model (1994–1996). As shown in panel A (table 6.7.2), its performance is consistent with the performance of the stale three-year model as there is no evidence of a systematic decline in performance across the ten-year test period. Further, the standard deviation of target concentration for both models (denoted SD (%) in table 6.7.2) can be considered moderate. The standard deviation of mean performance for the recursive model is 3.13% and the standard deviation of mean performance for the three-year model is 3.94%. This moderate standard deviation further attests to the relative stability of the long run performance of the stale model parameters.

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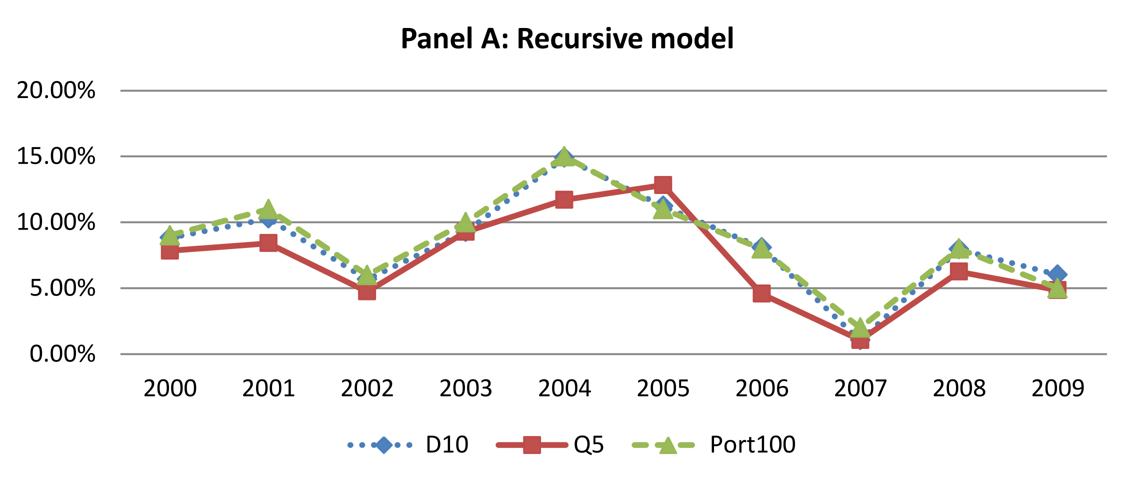
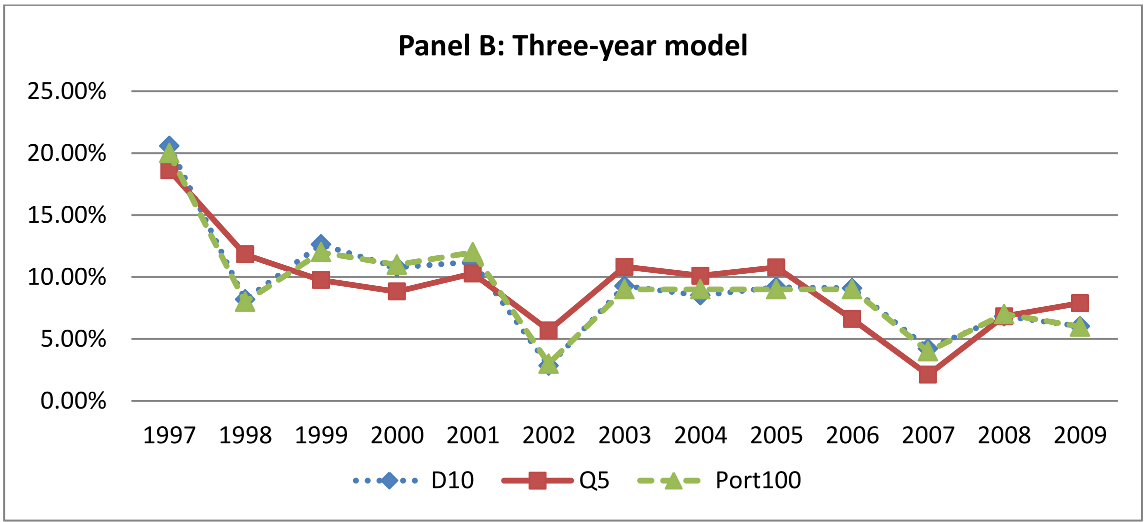
182 Data from 1994-1996 is used due to the small number of observations prior to this period. For example, the number of observations available for coefficient development between 1988 and 1990 is 101 observations. This increases slightly to 180 between 1991 and 1993. There are 2,129 available observations between 1994 and 1996. The reason for this is the fact that many firms do not report operating cash flow data pre-1994. Use of pre-1994 is therefore likely to bias results. Nonetheless, the conclusions do not change even when the model is developed using only pre-1994 data.

Table 6.7.2: The long run out-of-sample performance of stale model parameters





Panel C: Year on year performance

	Recursive model				Three-year model			
	D10 (%)	Q5 (%)	Port100 (%)	Mean (%)	D10 (%)	Q5 (%)	Port100 (%)	Mean (%)
1997					20.59	18.63	20.00	19.74
1998					8.18	11.82	8.00	9.33
1999					12.62	9.76	12.00	11.46
2000	8.82	7.84	9.00	8.56	10.78	8.82	11.00	10.20
2001	10.28	8.41	11.00	9.90	11.21	10.28	12.00	11.17
2002	5.66	4.74	6.00	5.47	2.83	5.69	3.00	3.84
2003	9.28	9.28	10.00	9.52	9.28	10.82	9.00	9.70
2004	14.89	11.70	15.00	13.87	8.51	10.11	9.00	9.21
2005	11.22	12.82	11.00	11.68	9.18	10.77	9.00	9.65
2006	8.08	4.57	8.00	6.88	9.09	6.60	9.00	8.23
2007	1.05	1.06	2.00	1.37	4.21	2.12	4.00	3.44
2008	7.95	6.25	8.00	7.40	6.82	6.82	7.00	6.88
2009	6.02	4.85	5.00	5.29	6.02	7.88	6.00	6.63
Mean	8.33	7.15	8.50	7.99	9.18	9.24	9.15	9.19
Std Dev	3.49	3.39	3.44	3.37	4.21	3.72	4.09	3.89

Notes: The table shows target concentrations (in percentages) achieved by stale (recursive and three-year) models in out of sample tests between 2000 – 2009 and 1997 – 2009, respectively. D10, Q5, Port100 are different portfolio selection criteria employed. Std Dev refers to the standard deviation of the target concentrations over the holdout period.

Overall, the results show that the performance of stale model parameters does not systematically decline over time. The implication is that model parameters developed in this study (model 15C, presented in table 6.2.1) can be potentially used by future researchers to ascribe takeover probabilities to UK firms. This is likely to reduce data collection costs while allowing future researchers to benefit from a developed and tested framework for assigning takeover probabilities. The conclusion from this analysis (i.e., the usefulness of current parameters for future prediction) is likely to persist until when there is a structural break in the characteristics of targets (see Pesaran and Timmerman (2002, 2007)). If such a break can be identified, it will, perhaps, be optimal to apply freshly developed model parameters[183].

This section has provided evidence to demonstrate that the performance of stale model parameters does not systematically decline over time. It could be suggested that, perhaps, the use of longer estimation windows in the development of stale model parameters will lead to better model training and hence, more stable parameters. Such parameters are likely to outperform stale parameters generated from short estimation windows. In section 6.7.3, I explore whether the length of the estimation sample affects the predictive ability of models employing stale parameters.

6.7.3 The effect of length of estimation period on parameter stability – stale models

To investigate whether the length of the estimation window affects the performance of stale model parameters, I compare the performance of three-year (short estimation window) models and recursive (long estimation window) models employing stale parameters. To achieve this, I compare the performance of (1) a three-year model which uses parameters estimated using data from 1997 to 1999 and predicts targets annually from 2000 to 2009 to (2) a recursive model whose parameters are estimated using data from 1988 to 1999 and predicts targets from 2000 to 2009. The difference in performance between (1) and (2) can directly be attributed to the effect of the length of the estimation window. The results of the analyses are shown in table 6.7.3.

183 The performance of 'stale' and 'fresh' parameters over the sample period is directly compared in section 6.8.4.

Table 6.7.3: Investigating the effect of the length of the estimation period on model performance

	Long estimation window			Short estimation window			Diff in conc. (%)	
	Pred.	Targets	Conc. (%)	Pred.	Targets	Conc. (%)	Diff. (pp)	P. value
D10	970	81	8.36	970	71	7.32	1.04	0.1749
Q5	1,936	139	7.19	1,936	144	7.44	-0.25	0.5421
Port100	1,000	85	8.50	1,000	71	7.10	1.40	0.1053
Port50	500	49	9.80	500	34	6.80	3.00***	0.0017
Port30	300	32	10.67	300	20	6.67	4.00**	0.0239
Port10	100	7	7.00	100	8	8.00	-1.00	0.6783
Port5%	487	49	10.06	488	34	6.97	3.09***	0.0013
Sample	**9,659**	**613**	**6.35**	**9,659**	**613**	**6.35**	**0.00**	**1.0000**
Overall	**5,293**	**442**	**8.35**	**5,294**	**382**	**7.22**	**1.13*** **	**0.0045**

Notes: The table presents summary results from out-of-sample predictions of the stale new model derived from long and short estimation windows. It compares the performance of (1) a three-year model which uses parameters estimated using data from 1997 to 1999 and predicts targets annually from 2000 to 2009 to (2) a recursive model whose parameters are estimated using data from 1988 to 1999 and predicts targets from 2000 to 2009. (1) is described as short estimation window and (2) is described as long estimation window. The difference in performance between (1) and (2) can directly be attributed to the effect of the length of the estimation window. Firms are ranked by their (predicted) takeover likelihood and firms with the highest takeover likelihood are selected as potential targets. Different criteria (Port100, Port50, Port30, Port10, D10, Q5 and Cut off) are used to determine what number of potential targets to select. Port100, Port50, Port30, and Port10 are portfolios of 100, 50, 30 and 10 firms with the highest probability of receiving the bids. D10 and Q5 are the 'top' decile and quintile portfolios respectively. Pred. is the number of predicted targets. Targets is the number of actual targets within Pred. Conc.% is the ratio (%) of Target to Pred. *t*-test for paired samples is used to compare the target concentrations achieved by the different models over the 10-year out of sample period spanning 2000 to 2009. 'Overall' represents the 'average' performance of each model. 'Sample' represents the performance of a model which simply predicts that every firm in the population is a takeover target. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

The performance of the model employing a long estimation window (1988–1999) is compared with the performance of a model using a short estimation window (1997–1999) in table 6.7.3. The two models, presumable, apply stale parameters as they are tested recurrently (without parameter redevelopment) over a ten year period (2000–2009). The results show that the stale model which employs a short estimation underperforms the model which employs a long estimation window. The model with the long estimation window achieves an overall target concentration of 8.35% as against 7.22% achieved by the model which employs a short estimation window. The difference in performance or target concentration (1.13 pp) is significant at the 1% level. The level of outperformance is evident in three out of seven portfolios (including Port50, Port30 and Port5%). The results from table 6.7.3 suggests that, in terms of predictive ability of stale models, stale models developed using long estimation windows are more robust that those developed using short estimation windows.

Section 6.7.2 showed that the predictive ability of stale models does not systematically decline over time. Section 6.7.3 showed that the length of the estimation window affects the predictive ability of stale model parameters. The next section (section 6.7.4) takes this assessment a step forward by evaluating whether fresh model parameters have any predictive advantage over stale model parameters.

6.7.4 The performance of stale model parameters versus fresh model parameters

The 'fresh' recursive model refers to a model whose parameters are redeveloped every year such that they take account of the most recently available firm data. In this case, the first fresh model is developed using data from 1988–1999. This model is used to predict targets in 2000. The model is again redeveloped to incorporate data for 2000 (i.e., estimation sample; 1988–2000), and the new (or fresh) parameters are used to predict targets in 2001. This recursive process is followed every year up until 2008. The 'stale' recursive model, on the other hand, uses fixed parameters developed from data in the estimation period 1988 to 1999 to predict targets in consecutive years between 2000 and 2009. Presumably, the model is 'stale' as it does not include new information to make predictions in subsequent years. For example, the model uses coefficients developed from the 1988–1999 data to make predictions in 2009. The target concentration achieved across different portfolios is computed as the ratio of actual targets predicted to the total number of predictions. The performance of the stale model in comparison to the fresh model (across different portfolio selection criteria) over the ten-year holdout sample period is shown in table 6.7.4.

Table 6.7.4: Comparing the performance of stale and fresh model parameters.

	Fresh parameters			Stale parameters			Diff in Conc.	
	Pred.	Targets	Conc.(%)	Pred.	Targets	Conc.(%)	Diff. (pp)	P. value
D10	969	88	9.08	969	81	8.36	0.72	0.1401
Q5	1,933	161	8.33	1,933	139	7.19	1.14**	0.0371
Port100	1,000	91	9.10	1,000	85	8.50	0.60	0.2967
Port50	500	49	9.80	500	49	9.80	0.00	1.0000
Port30	300	24	8.00	300	32	10.67	-2.67	0.1039
Port10	100	7	7.00	100	7	7.00	0.00	1.0000
Port5%	487	47	9.65	487	49	10.06	-0.41	0.6462
Overall	**5,289**	**467**	**8.83**	**5,289**	**442**	**8.36**	**0.47**	**0.8580**
Sample	**9,647**	**612**	**6.34**	**9,647**	**612**	**6.34**	**0.00**	**1.0000**

Notes: The table presents summary results from out-of-sample predictions of the new model derived from fresh and stale parameters. It compares the performance of (1) a model which uses parameters estimated using data from 1989 to 1999 and predicts targets annually from 2000 to 2009 – stale parameters – to (2) a model whose parameters are estimated in a recursive manner using data from 1988 and predicts targets out-of-sample from 2000 to 2009 – fresh parameters. The difference in performance between (1) and (2) can directly be attributed to the effect of the 'staleness' of model parameters. Firms are ranked by their (predicted) takeover likelihood and firms with the highest takeover likelihood are selected as potential targets. Different criteria (Port100, Port50, Port30, Port10, D10, Q5 and Cut off) are used to determine what number of potential targets to select. Port100, Port50, Port30, and Port10 are portfolios of 100, 50, 30 and 10 firms with the highest probability of receiving the bids. D10 and Q5 are the 'top' decile and quintile portfolios respectively. Pred. is the number of predicted targets. Targets is the number of actual targets within Pred. Conc.% is the ratio (%) of Target to Pred. *t*-test for paired samples is used to compare the target concentrations achieved by the different models over the 10-year out of sample period spanning 2000 to 2009. 'Overall' represents the 'average' performance of each model. 'Sample' represents the performance of a model which simply predicts that every firm in the population is a takeover target. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

The fresh parameters outperform the stale parameters across a majority of portfolio selection criteria. The fresh parameters are able to correctly predict 25 (or 5.67%) more targets compared to the stale parameters over the 10 year period. Nonetheless, the difference in target concentration (0.47 pp) achieved by the two models is not significant at the 10% level. The results suggest that despite the finding that stale model parameters have considerable predictive power (as discussed in section 6.7.2), prediction with fresh parameters, whenever possible, is likely to lead to more optimal results.

This section (section 6.7.4) has revealed that fresh model parameters have a higher predictive ability when compared with stale model parameters. While fresh model parameters are clearly the more optimal choice (e.g., from an investors perspective), the evidence suggests that stale parameters can still be useful in ascribing takeover probabilities (e.g., from a researcher's perspective). The usefulness of the new model's stale parameters to future researchers (for example) is further explored in section 6.7.5. Section 6.7.5 evaluates whether the new model still outperforms the old model (as discussed in sections 6.2 and 6.3) when stale model parameters are applied.

6.7.5 Old versus new model suitability for future prediction – stale models

Section 6.7.2 suggested that stale model parameters can still be useful in the prediction of future targets or in ascribing firm takeover probabilities in the future. Such application of stale parameters is likely to substantially reduce the cost of data collection and model building. In this section, the old model is compared with the new model based on their predictive abilities when stale model parameters are employed. This will allow for a recommendation to be made on what model to apply when stale parameters are being employed. Table 6.7.5 compares the performance of a stale new model and that of a stale old model. The two models are developed using data from 1989 to 1999 and tested for predictive ability over the ten-year period from 2000 to 2009. The variables in the old (new) model are similar to those in model 15A (15C) in table 6.2.1a. The results from the analysis are shown in table 6.7.5.

The results in table 6.7.5 show that the stale new model substantially outperforms the stale old model on average. The stale new model achieves an overall target concentration of 8.36% over the 10-year period (2000–2009) as compared to 6.90% achieved by the stale old model over the same period. The difference in target concentration (14 more correct predictions or 1.46 pp) is significant at the 5% level. The result achieved across different portfolios is consistent with the argument that the new model (with stale parameters) has a superior predictive ability when compared to the old model (with stale parameters). Overall, the findings in this section support the use of the new model over the old model when stale parameters are being adopted. These results are also consistent with earlier conclusions that the new model has a superior predictive ability when compared to the old model (see section 6.2 and 6.3).

Table 6.7.5: Comparing the performance of old and new models which employ stale parameters

	New model			Old model			Diff. in Conc. %	
	Pred.	Targets	Conc.%	Pred.	Targets	Conc.%	Diff. (pp)	P. value
D10	969	81	8.36	1,230	86	6.99	1.37	0.2664
Q5	1,933	139	7.19	2,455	160	6.52	0.67	0.5137
Port100	1,000	85	8.50	1,000	74	7.40	1.10	0.3711
Port50	500	49	9.80	500	35	7.00	2.80**	0.0128
Port30	300	32	10.67	300	23	7.67	3.00*	0.0676
Port10	100	7	7.00	100	9	9.00	-2.00	0.4433
Port5	487	49	10.06	618	41	6.63	3.43**	0.0168
Overall	**5,289**	**442**	**8.36**	**6,203**	**428**	**6.90**	**1.46****	**0.0101**
Sample	**9,647**	**612**	**6.34**	**12,249**	**747**	**6.10**	**0.25**	**0.2957**

Notes: The table presents summary results from out-of-sample predictions of the new and old models derived from stale parameters. Firms are ranked by their (predicted) takeover likelihood and firms with the highest takeover likelihood are selected as potential targets. Different criteria (Port100, Port50, Port30, Port10, D10, Q5 and Cut off) are used to determine what number of potential targets to select. Port100, Port50, Port30, and Port10 are portfolios of 100, 50, 30 and 10 firms with the highest probability of receiving the bids. D10 and Q5 are the 'top' decile and quintile portfolios respectively. Pred. is the number of predicted targets. Targets is the number of actual targets within Pred. Conc.% is the ratio (%) of Target to Pred. *t*-test for paired samples is used to compare the target concentrations achieved by the different models over the 10-year out of sample period spanning 2000 to 2009. 'Overall' represents the 'average' performance of each model. 'Sample' represents the performance of a model which simply predicts that every firm in the population is a takeover target. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

6.8 The choice of portfolio selection criteria

Little has been said about how to identify an optimal cut-off point across the prediction and forecasting literature. The convention is for researchers to employ deciles, quintiles and percentiles (see, for example, Cremers et al. (2009), Brar et al. (2009) and Cornett et al. (2011)). Other researchers (such as Palepu (1986), Barnes (1990, 1999, 2000) and Powell (2001, 2004)) have proposed the use of optimal cut-off probabilities derived ex ante. As discussed in section 4.4.5, the use of the 25th percentile (Cornett et al. (2011)), deciles (Brar et al. (2009)) and quintiles (Cremers et al. (2009)) is, perhaps, arbitrary as it integrally assumes that 25% (25th percentile), 10% (deciles) or 20% (quintiles) of listed firms within the holdout sample are likely to receive takeover bids in each year. The empirical analysis in this study showed that on average only about 5.05% of UK firms received bids annually between 1988 and 2009[184]. In addition to deciles, quintiles and

[184] This level of UK M&A activity is similar to the 5.00% (between 1986 and 1995) reported by Powell (2004). This level of activity is higher than the level reported in the US. For example, Cornet

optimal cut-off probabilities, I considered the diversity of potential model users, and employed other portfolio selection techniques including Port100, Port50, Port30, Port10 and Port5% (fully discussed in table 4.4.5).

The results from the analyses in this chapter reveal some differences in performance across these portfolio selection methods. The main difference between these portfolios is the number of potential targets each portfolio selects. In general, the use of deciles (D10), quintiles (Q5), Port5% and Port100 allow for the selection of a higher number of firms as potential targets. This implies a higher likelihood of correctly predicting a target, but also a substantial level of type II errors (i.e., non-targets predicted as targets). Such portfolios appear to be less risky as they are less likely to achieve zero target concentrations. Port30 and Port10 can be considered 'high risk' portfolios as the likelihood of correctly predicting a target is lower than in the larger portfolios. Nonetheless, in these smaller portfolios, the impact of correctly predicting a target is higher and the level of potential misclassification is substantially less. For example, a correct prediction of one target when Port10 is being employed results in a target concentration of 10%.

To assess and compare the performance of the portfolios, I adopt a simple ranking procedure which is analogous to the Wilcoxon Rank-Sum non-parametric test. This procedure involves ranking the eight portfolio selection procedures applied in this study (D10, Q5, Port5%, Port100, Port50, Port30, Port 10 and cut-off probabilities) across five key performance measures. These performance measures include: overall (mean) target concentration achieved, median target concentration achieved, maximum target concentration achieved, minimum target concentration achieved, and the standard deviation of target concentrations over the period. The mean and median target concentration achieved is a measure of long run performance. The maximum, minimum and standard deviation of target concentrations represent the level of variability in the performance (an indication of risk). The results obtained from the new (model 15C) and old (model 15A) model in out-of-sample predictions between 1995 and 2009 are used in this analysis. Table 6.8.1 presents a summary of these results and the rankings achieved by the different portfolio selection techniques.

et al. (2011) report that 2.87% of listed US firms are targets between 1975 and 2004. An early study by Palepu (1986) reports a level of M&A activity of about 2.6% in 1979.

Table 6.8.1: Assessing the performance of different portfolio selection criteria.

	Mean %	Median %	Min %	Max %	Std. Dev. %	Sum of ranks
Panel A: New model						
D10	10.47	10.23	2.11	20.59	4.70	29.00
Q5	9.96	9.79	2.65	20.10	4.19	24.00
Port100	10.40	10.00	2.00	20.00	4.59	21.50
Port50	11.20	10.00	2.00	26.00	6.32	25.00
Port30	10.89	10.00	3.33	30.00	7.74	28.50
Port10	9.33	10.00	0.00	40.00	10.62	18.00
Cut off	8.12	6.98	0.00	20.00	6.05	10.00
Port5%	11.23	9.62	2.08	27.45	6.52	24.00
Panel B: Old model						
D10	8.37	7.69	2.27	17.29	4.05	27.50
Q5	7.93	7.20	2.27	15.85	3.14	21.50
Port100	8.13	7.00	1.00	16.00	4.15	18.50
Port50	8.13	8.00	2.00	18.00	4.92	23.50
Port30	8.89	6.67	3.33	20.00	5.92	26.50
Port10	8.00	10.00	0.00	20.00	6.53	20.50
Cut off	9.19	9.85	0.85	18.64	4.64	28.00
Port5%	7.85	6.35	1.52	17.54	4.89	14.00

Notes: The table assesses the performance of different selection criteria across five key performance measures: overall target concentration achieved (Mean. %), median target concentration achieved (Median %), maximum target concentration achieved (Max. %), minimum target concentration achieved (Min. %), and the standard deviation of target concentrations over the period (Std. Dev. %). The best criterion is given a rank of eight and the worst criterion is given a rank of one. The ranks for each selection criterion across the different performance measures are added up to arrive at the Sum of ranks.

The results from panel A and B, show that, on average, Port10 and Port30 report the highest standard deviation. This indicates a substantial variation in their performance from one year to another. Port5% and Port50 report the highest overall (long run) target concentrations (11.23% and 11.20%, respectively). The larger portfolios (D10, Q5 and Port100) achieve lower variation (or more stability) in their performance from one year to another. The results from panel B indicate that the larger portfolios (Port100, Q5 and D10) also report a higher minimum target concentration, on average.

The results from the sum of ranks show that the larger portfolios (Port100, D10 and Q5) perform best when different parameters including overall (mean and median) concentration of targets in the portfolio, maximum target concentration achieved, minimum target concentration achieved and standard deviation of target concentration are considered. The smaller portfolios (e.g., Port10) tend to achieve the lowest ranks (or score) across all criteria. They appear to perform at extremes achieving high target concentration in certain years and low (or even zero) target concentration in other years. Overall, the findings suggest that portfolio selection techniques which generate larger portfolios (e.g., D10) are more optimal as they result in slightly better long run performance and lower variability in performance. The selection of smaller target portfolios results in a high level of variability and inconsistency in the models' performance.

6.9 Chapter summary and conclusion

The primary goal of this chapter is to evaluate the performance of the new model developed in this study in terms of its ability to correctly classify targets and non-targets and its ability to correctly predict firms that will receive bids in a holdout sample. To achieve this goal, the performance of the old model is compared to the performance of a benchmark model – the old model. Another key objective of this chapter is to empirically determine an optimal modelling strategy in terms of the length of the estimation period in predictive model development and the optimal choice of portfolio selection techniques. The final objective of the chapter is to investigate the usability of stale model parameters in target prediction several years ahead.

The evidence shows that the new variables introduced in this study improve the old model's ability to correctly classify target and non-target firms within-sample and to correctly predict target firms out-of-sample. The new model outperforms the old model when the AUC is assessed and when their abilities to predict targets in a hold-out sample is compared. The implication is that the model more fully explains the differences between UK targets and non-targets. The results also confirm that the new model outperforms the old and old (balanced) models in out-of-sample prediction tests across a wide variety of scenarios or modelling choices. The results in this study compare favourably with comparable prior studies including Barnes (1998, 1999, 2000) and Powell (1997, 2001, 2004).

In critique of prior studies, I find that the performance of prediction models substantially vary from one year to another between 1995 and 2009. This performance appears to be positively correlated with the overall market (FTSE all-share index) performance. I find that the performance achieved by the models is higher in bull market periods and lower in bear market periods. These results suggest that the use of a one-year out-of-sample test period (such as in Palepu (1986), Barnes (1998, 1999, 2000) and Powell (2001, 2004), amongst others) leads to non-robust and non-generalisable conclusions. In this respect, I propose that the approach to model out-of-sample testing adopted in this study, provides a more reliable test of model out-of-sample predictive ability.

Again, I find that the use of longer estimation windows do not necessarily result in better predictive abilities for either the new or the old model. This finding suggests that the choice of estimation windows and selection criteria applied in prior research is, perhaps, arbitrary. The results also show that the use of portfolio selection techniques which lead to the prediction of a large number of targets (e.g., Port100, D10 and Q5) is a more optimal modelling strategy when the goal is to achieve the high target concentrations, with no consideration made for resulting transaction costs. I find that selection criteria which lead to the selection of a small number of targets (such as Port10 and Port30) lead to unstable and highly variable results.

Finally, I find that stale model parameters retain predictive ability which does not systematically decline over time. This finding suggests that (stale) model parameters developed in this study can be used in future studies (constraint by data collection costs) to ascribe takeover likelihood to UK firms (see, for example, model 15C, table 6.2.1). This also suggests that these coefficients are, to some extent, robust over time. The stale parameters appear to perform better when longer estimation windows are applied. Notwithstanding, the results suggest that fresh model parameters have an added predictive power over stale model parameters. The implication is that fresh model parameters should be developed whenever possible. Overall, the results achieved in this chapter contribute to the literature by ascertaining that the new model is more ‘efficient’ than earlier models. It also contributes to the literature by exploring the importance of modelling choices (such as the length of the estimation window, the portfolio selection criteria and the use of stale versus fresh model parameters) in the development of optimal prediction models.

While the new model is more efficient in predicting takeover targets compared to the old model as shown by the empirical results, it is uncertain whether an investor can use the new model to outperform the market. The focus of chapter 7 is therefore to investigate whether the new model, with its superior predictive ability, can form the basis of a profitable investment strategy.

CHAPTER 7 INVESTING IN PREDICTED TARGETS

7.1 Overview

A new takeover prediction model is developed and tested in chapter 6. The results suggest that this new model (and the new variables) improves the classification and predictive ability of takeover prediction models employed in prior studies. Interestingly, the results from chapter 6 indicate that target concentration of up to 11.23% could be achieved by holding a portfolio of the 5th percentile of firms with the highest takeover likelihood as ascribed by the new model over the period 1995 to 2009. While this appears like a moderate level of performance, it represents a substantial improvement on prior prediction models which generally attained concentrations of about 3% or less, on average (see, for example, Palepu (1986), Walter (1994), Barnes (1998, 1999, 2000), Powell (1997, 2001, 2004), and Brar et al. (2009)), amongst others). It is also a substantial improvement over a random selection approach, given that targets make up about 5.05% of the population of firms in the sample each year (see section 4.2.6).

As discussed in the section 2.3.3, there is a consensus within the literature that significant abnormal returns accrue to takeover targets (Huang and Walkling (1987), Bradley et al. (1988), Frank and Harris (1989), Parkinson and Shaw (1991), Stulz et al. (1990), Schwert (2000), Parkinson and Dobbins (1993), Moeller (2005), Cornett et al. (2011) and Danbolt and Maciver (2012)). This chapter builds on this finding by investigating whether the new model (general version with continuously updated coefficients) can form the basis of a profitable investment strategy. This evaluation is critical for investors such as fund managers who are looking for superior investment strategies.

To an extent, testing whether superior returns can be generated from takeover prediction modelling can serve as a test of the Efficient Market Hypothesis (EMH – semi strong form). A finding that abnormal returns can be generated (consistently and over the long run) from an investment strategy focusing on investing in predicted targets will be inconsistent with the predictions of the EMH. This is because the (new) model employs publicly available information, which, per the EMH, should already be discounted in stock prices.

As in the previous chapter, several different portfolios are analysed for robustness, and the results obtained using the new model are compared with those from the old. The version of the new model employed in this chapter is that which uses all the new variables. This decision is based on the finding (in sections 6.2.3 and 6.2.4) that the general new model (which includes all the new variables) slightly outperforms a more restricted new model (which excludes non-significant variables). The methodology employed in this chapter (including the computation of returns and the formation of portfolios) is discussed in sections 4.4 and 4.5. In section 7.2, the risk-adjusted returns generated by the new model are presented and discussed. In section 7.3, the new model's potential to generate returns for investors is compared with that of the old model. Section 7.4 presents further analysis aimed at explaining some of the key results obtained in the chapter. Section 7.5 concludes the chapter and discusses some of its implications to research and practice.

7.2 The returns generated by the new model

7.2.1 Overview

The main interest of this chapter is to evaluate whether the new model can inform a profitable investment strategy. This section investigates whether the new model can generate positive returns for investors by investigating its performance in backtests – i.e., retrospective evaluation of annual investment performance. The use of backtests to provide evidence on potential model performance is in line with the literature (see, for example, Cahan et al. (2011) and Cremers et al. (2009)). The procedure for computing portfolio returns is fully discussed in chapter 4. Stocks predicted as potential takeover targets based on their financial statements – assumed to be available on 30 June X1 – are placed within a portfolio (target portfolio) and the discrete monthly returns on each stock within the target portfolio from July X1 to June X2 are computed. Both equal weighted and value weighted portfolio returns are computed from the discrete monthly returns of all firms within the portfolio. Equal weighted portfolio returns for each month is the arithmetic average of the returns to all the stocks within the portfolio in that month. Value weighted returns are computed by weighting stocks with respect to their market value at the start of the holding period (30 June X1). No monthly rebalancing is applied.

Risk-adjusted portfolio returns (employing different risk adjustment methodologies, such as the capital asset pricing, Fama and French three factor and Carhart four factor models) are used in the evaluation. These different methodologies are fully discussed in section 4.5.

I focus on the different portfolios (deciles, quintiles, Port100, Port50, Port30, Port10 and Port5%) that were developed in chapter 6. The returns generated by these portfolios are presented and discussed in the sections below.

7.2.2 Average Monthly Risk-Adjusted Returns (AMRR)

In this section, the simple calendar time portfolio (monthly) returns (AMUR) generated by the model are adjusted for risk using factor models. The methodology applied is fully discussed in section 4.5.3. It is consistent with Ang and Zhang (2004). The methodology involves regressing the excess equal and value-weighted portfolios returns (AMUR – RF) on the monthly factors (RM–RF, SMB, HML, UMD) in the four factor model (Carhart (1996)). The regression model (equation 4.5.3 (3)) is shown below;

$$R_{it} - RF_t = \alpha_i + \beta_{mkt}(RM_t - RF_t) + \gamma_{smb}SMB_t + \tau_{hml}HML_t + \rho_{umd}UMD_t + \varepsilon_{i,t} \ldots\ldots Eqn\ 4.5.3(3)$$

In these equation, R_{it} is the discrete return (AMUR) on portfolio *i* in month *t*, RF_t is the risk free rate in month *t*, α_t is the abnormal (excess) monthly return or portfolio alpha in the period, RM_t is the market return in month *t*, SMB (Small Minus Big) and HML (High Minus Low) are the Fama & French factors, UMD (Winners Minus Losers) is the momentum factor. SMB (the difference in the returns of value-weighted portfolios of small stocks and big stocks), HML (the difference in the returns of value-weighted portfolios of high book-to-market stocks and low book-to-market stocks) and UMD (the difference in the returns of winners and losers) depict the monthly return on the zero investment portfolio for the common size factor, book to market equity factor and momentum factor in stock returns. $\beta, \gamma, \tau, \rho$ are regression coefficients for the different risk factors. The data for the monthly risk free rate (RF), the monthly market return (RM), and the risk factors (SMB, HML and UMD) for the UK market are obtained from Gregory et al. (2013).

Table 7.2.2a presents the results obtained when a continuously-updated model (or recursive modelling strategy) is used to predict potential targets from 1995 to 2009 and a decile optimal portfolio selection strategy is used to select the target portfolio. For robustness, results obtained using other factor models – the CAPM and the Fama and French three-factor model – are also presented.

Table 7.2.2a: Regression coefficients from decile portfolios: 1995 to 2009

	(1) Equal Weighted D10 Portfolio			(2) Value Weighted D10 Portfolio		
	CAPM	FF3F	Carhart	CAPM	FF3F	Carhart
Alpha	0.005	0.004	0.003	0.005	0.005	0.006*
RM - RF	1.005***	0.875***	0.895***	1.035***	0.951***	0.939***
SMB		1.234***	1.260***		0.797***	0.783***
HML		-0.076	-0.001		-0.041	-0.083
UMD			0.098			-0.055

Notes: The table presents results for cross sectional regression of portfolio returns on return-generation factors (CAPM, Fama and French three Factor and Carhart model factors). The regression model (eqn. 4.5.3(3)) is shown below:

$$(R_{it} - RF_t) = \alpha_i + \beta_{mkt}(RM_t - RF_t) + \gamma_{smb}SMB_t + \tau_{hml}HML_t + \rho_{umd}UMD_t + \varepsilon_{i,t}$$

The dependent variable is $(R_{it} - RF_t)$ where R_{it} is the equal (1) or value (2) weighted return on the portfolio and RF_t is the risk free rate. The independent variables include the factors in the Carhart model; RM - RF (excess market return), SMB (size factor), HML (book to market factor) and UMD (momentum factor). See Carhart (1997) and Fama and French (1993) for a discussion. UK Data for these factors (including the UK risk free rate) is provided by Gregory et al. (2013). The portfolio holding period is 180 months from July 1996 to June 2011. The estimate of the intercept term 'Alpha' provides a test of the null hypothesis that the mean monthly excess return on the calendar-time portfolio is zero. ***, **, * indicate significance at 1%, 5% and 10%, respectively.

The results obtained using the decile portfolio selection strategy show that the portfolios generate average monthly excess returns (or alphas) of 0.3% (equal-weighted portfolio) and 0.6% (value-weighted portfolio) during the July 1996 to June 2011 holding period. The alpha generated by the equal-weighted portfolios is insignificant while that generated by the value-weighted portfolios is significant (at the 10% level) using the Carhart model. These results suggest that takeover prediction as investment strategy is potentially profitable in certain instances. Nonetheless, further tests are needed to explore this finding. The first test conducted is to investigate whether the results are shaped by the portfolio formation strategy. Table 7.2.2b presents summary results obtained when different portfolio formation strategies (including quintiles, fixed portfolios and cut-offs) are employed. For simplicity, only the portfolio alphas generated from different factor models are presented.

Table 7.2.2b: Abnormal returns (alphas) generated by the new model

Panel A: Portfolio Alpha - Equal Weighted				
	Target conc.%	CAPM	FF3F	Carhart
D10	10.47	0.005	0.004	0.003
Q5	9.96	0.005	0.004	0.003
Port100	10.40	0.005	0.005	0.004
Port50	11.20	0.006	0.005	0.005
Port30	10.89	0.006	0.005	0.004
Port10	9.33	0.006	0.007	0.004
CUT OFF	8.12	-0.018**	-0.020***	-0.023***
Port5%	11.23	0.004	0.004	0.003
Average	**10.20*** **	**0.002*** **	**0.002*** **	**0.000*** **
Median	**10.44**	**0.005**	**0.005**	**0.004**

Panel B: Portfolio Alpha - Value Weighted				
	Target conc.%	CAPM	FF3F	Carhart
D10	10.47	0.005	0.005	0.006*
Q5	9.96	0.005	0.004	0.005*
Port100	10.40	0.005	0.004	0.005
Port50	11.20	0.006	0.007	0.008
Port30	10.89	0.008	0.008	0.009
Port10	9.33	0.005	0.005	0.007
CUT OFF	8.12	-0.020**	-0.022***	-0.023***
Port5%	11.23	0.006	0.006	0.007
Average	**10.20*** **	**0.003*** **	**0.002*** **	**0.003*** **
Median	**10.44**	**0.005**	**0.005**	**0.007**

Note: The table presents alphas (constant term and significance) for cross sectional regression of portfolio returns on return-generation factors (CAPM, Fama and French three Factor and Carhart model factors) for different portfolio formation strategies. The regression model (eqn. 4.5.3(3)) is shown below:

$$(R_{it} - RF_t) = \alpha_i + \beta_{mkt}(RM_t - RF_t) + \gamma_{smb}SMB_t + \tau_{hml}HML_t + \rho_{umd}UMD_t + \varepsilon_{i,t}$$

The dependent variable is $(R_{it} - RF_t)$ where R_{it} is the equal (panel A) or value (panel B) weighted return on the respective portfolios (D10, Q5, Port100. Port50, Port30, Cut Off, Port5%) and RF_t is the risk free rate. The independent variables include the factors in the Carhart model; *RM - RF* (excess market return), *SMB* (size factor), *HML* (book to market factor) and *UMD* (momentum factor). See Carhart (1997) and Fama and French (1993) for a discussion. UK Data for these factors (including the UK risk free rate) is provided by Gregory et al. (2013). The portfolio holding period is 180 months from July 1996 to June 2011. Target Conc % represents the proportion of actual takeover targets within the portfolio. The estimate of the intercept term 'Alpha' provides a test of the null hypothesis that the mean monthly excess return on the calendar-time portfolio is zero. ***, **, * indicate significance at 1%, 5% and 10%, respectively.

Table 7.2.2b (panel A and B) show that the results (alpha) obtained using the Carhart model is not markedly different from those obtained using the CAPM or the Three Factor model. The results indicate that the new model is incapable of generating abnormal returns consistently across different portfolio formation strategies. The model generates positive abnormal returns (significant at the 10% level) only when value-weighted portfolios are applied and this is limited to the decile portfolio formation strategy. Some portfolios, like

Port30 and Port50 generate substantially higher alphas (insignificant at the 10% level) of up to 0.8% and 0.9% respectively. These alphas are, perhaps, insignificant because of the high volatility in the returns generated by the portfolios. Besides lacking statistical significance, these levels of returns (e.g., 0.5% per month) are also likely to be economically low. This will be further discussed in section 7.3.

The use of the cut-off portfolio formation strategy leads to the generation of significant negative alphas. This is, perhaps, because the use of cut-offs to identify target portfolio leads to the generation of very large target portfolios. As shown in table 6.3.1, when deciles (Port100) are used to generate target portfolios between 1995 and 2009, the target portfolio obtained consists of a total of 1,490 (1,500) predicted targets of which 156 (156) are actual targets. The target portfolio obtained using cut-offs consists of a total of 2,450 predicted targets of which 199 predicted targets actually receive takeover bid. The cut-off procedure generates an extremely low cut off probability of 0.047 using data from 1998 to 1994, leading to a prediction that 995 (from a sample of 1,031) firms will receive a bid in 1995, of which only 50 firms do. This, potentially, negatively impacts on the returns generated by the new model when cut-off probabilities are used.

On a whole, the evidence suggests that the new model cannot be consistently employed by investors to successfully generate significant positive returns in the long run. It generates positive abnormal returns in most instances but these returns are not statistically different from zero. The results are broadly consistent with the EMH, as it confirms that significant positive abnormal returns cannot be generated consistently, in the long run, by relying on investment strategies which employ publicly available information. These results are also consistent with the conclusions of Palepu (1986) and Powell (2001, 2004) who concede that abnormal returns can hardly be generated by using takeover prediction models.

While consistent with current theory and prior evidence, the results substantially extend prior literature by investigating the performance of the model over a significantly longer holding period (July 1996 to June 2011). This holding period is interspersed by substantial variations in overall market performance due to two sub-periods of market collapse – the dotcom crisis (after 2000) and the global financial crisis (after 2007). These periods are characterised by general falling prices and poor stock performance. Do these periods of crisis have an impact on (or explain) the reported results? Will the model perform differently if these periods were excluded from the analysis? That is, will investors be able to use the model successfully, if they restricted its use to non-crises periods? This test is further justified on the grounds that, outside the takeover prediction literature, several studies (for example, Maheu and McCurdy (2000), Pagan and Sossounov (2003) and Lunde and Timmerman (2004), amongst others) have developed models for the prediction of market cycles. Also, some takeover prediction researchers have restricted their investigations to particular time periods – usually one year. Does this have an impact on the reported results? I explore some of these pertinent questions in section 7.2.3.

7.2.3 Variability of portfolio returns

The result in section 7.2.2 suggests that, on average, the new takeover prediction model does not generate positive abnormal returns in backtests. These results are in line with the literature (Palepu (1986), Powell (2001, 2004)) but employ more robust analyses, over a long time period. Palepu (1986) and Powell (2001, 2004) arrive at their conclusion by testing model performance in a single year. In section 6.5, this approach was criticised and empirical evidence was presented to show that conclusions based on the approach lacked robustness and generalisability. The results in section 7.2.2 are based on long run average performance. That is, the model's performance is tested over 15 years (180 months) and the average performance over this period is reported. In this section, I present results (in support of my critique of prior studies in section 6.5.) to show that performance substantially varies from one period to another.

Further, the returns to the portfolios in this study appear to be driven by overall market trends. This is particularly the case as a substantial proportion of the portfolios (over 90% in several cases, as shown in table 6.3.1) are made up of firms which do not receive a bid during the period. While actual targets can be expected to generate abnormal returns upon bid announcements (further tested in section 7.4), the average non-target within predicted target portfolios can be expected to earn returns in line with the market (further analysed in section 7.4). The high number of non-targets together with their moderate performance (as will be shown in section 7.4) is likely to neutralise any returns generated by actual targets within the portfolio. The implication is that the portfolios will, perhaps, generate positive unadjusted returns in bull periods and negative unadjusted returns in bear periods as the non-targets within the portfolio earn returns, broadly, in line with the market. It is unclear whether these returns, when adjusted for risk, will be statistically different from zero (this is further investigated below).

Further, the results in section 6.5.3 revealed that the models achieve higher target concentrations in bull periods as compared to bear periods. In section 6.5.3, I argue (in line with Harford (2005)) that this is partly driven by higher market liquidity and a greater incentive to engage in mergers in bull periods. (This issue is further discussed in the development of the market economics hypothesis in section 3.3.12). These higher target concentrations achieved during bull periods, all things being equal, should also lead to higher portfolio returns in bull periods as compared to bear periods. Interestingly, there is a growing literature on the prediction of bull and bear markets (see, for example, Pagan and Sossounov (2003) and Lunde and Timmerman (2004), amongst others). If indeed, a prediction model can generate higher returns during bull periods (to be investigated), then it is worth exploring whether a two-stage prediction strategy can be of some benefit to investors. In this case, the first stage of the strategy will involve predicting market cycles and the second stage of the model will involve predicting takeover targets. The prediction of macroeconomic cycles generally involves the use of time series models (such as GARCH models) which are fundamentally different from the logit regression models employed in this study. Combining the logit and GARCH model in a single modelling framework is likely to present a significant challenge. This study does not pursue this line of enquiry.

The goal here is to evaluate whether the results obtained above (i.e., the model's inability to consistently outperform the market) remain robust even when only periods of market growth (bull markets) are considered. To test this, I employ a simple approach to distinguish between bull and bear periods and investigate whether portfolio performance is enhanced in bull periods as compared to bear period. It is worth stating that several methods for identifying (or predicting) bull and bear markets trends have been proposed in the literature. While models such as the Markov-Switching and GARCH models provide an advanced and more efficient method for identifying different regimes (see, for example, Maheu and McCurdy (2000)), a simple ex-post assessment of price index peaks and troughs (dating algorithm) is, perhaps, sufficient for the purpose of this study[185]. This form of assessment assumes perfect foresight of future regime changes and is, therefore, over-optimistic. Similar dating algorithms have been proposed and used in studies such as Pagan and Sossounov (2003) and Lunde and Timmerman (2004). The task here is not to predict bull and bear periods and hence, I benefit from hindsight by identifying bull and bear periods based on cumulative market returns (following Lunde and Timmerman (2004)).

[185] The prediction of Bull and Bear periods is beyond the scope of the current study.

Figure 6.5.3 plots the cumulative return on the FTSE All-Share index from 1991 to 2010. As discussed in section 6.5.3, one can approximate the start and end of bull and bear periods by using cumulative market (FTSE All-Share index) returns over time. From figure 6.5.3, two major periods of market decline are evident: post–2000 and post–2007. These periods coincide with the dotcom crisis and the global financial crisis periods. Ignoring short term or secondary trends, and considering the size of the change in cumulative market return, one can identify two major bull periods (BULL 1 and BULL 2) and two major bear periods (BEAR 1 and BEAR 2). BULL 1 is considered as the period between June 1994 and August 2000. This bull period (BULL 1) is followed by a bear period (BEAR 1) which runs from September 2000 to March 2003. BEAR 1 is followed by a bull period which runs from April 2003 to October 2007. The period post October 2007 (October 2007 to June 2010) has been considered as a Bear Period for the purpose of this study. The short period of market growth post August 2008 is ignored as it does not give sufficient observations for robust time series regression analysis. Table 7.2.3a and 7.2.3b shows the alphas generated by the new model over different market states.

Table 7.2.3a: Abnormal returns (alphas) generated by the new model during bull and bear periods

Panel A: Equal-Weighted D10 Portfolio				
	BULL 1	BEAR 1	BULL 2	BEAR 2
Alpha	0.034***	0.013*	-0.004	-0.041***
RM - RF	0.741***	0.956***	0.916***	0.846***
SMB	1.133***	1.353***	1.259***	0.995***
HML	-0.579***	0.514***	0.499	0.258
UMD	-0.051	0.006	-0.540**	0.075
Panel B: Value-Weighted D10 Portfolio				
	BULL 1	BEAR 1	BULL 2	BEAR 2
Alpha	0.028***	0.009	-0.003	-0.027***
RM - RF	0.662***	0.912***	1.122***	1.076***
SMB	0.471***	1.018***	1.023***	0.460***
HML	-0.531***	0.510**	-0.164	-0.173
UMD	-0.070	-0.109	-0.461***	-0.223**
N (Months)	50	31	55	44

Notes: The table presents results for cross sectional regression of portfolio returns on return-generation factors (Carhart model factors) when portfolios are formed using deciles. The regression model (eqn. 4.5.3(3)) is shown below:

$$(R_{it} - RF_t) = \alpha_i + \beta_{mkt}(RM_t - RF_t) + \gamma_{smb}SMB_t + \tau_{hml}HML_t + \rho_{umd}UMD_t + \varepsilon_{i,t}$$

The dependent variable is $(R_{it} - RF_t)$ where R_{it} is the equal (panel A) or value (panel B) weighted return on the decile portfolio and RF_t is the risk free rate. The independent variables include the factors in the Carhart model; *RM - RF* (excess market return), *SMB* (size factor), *HML* (book to market factor) and *UMD* (momentum factor). See Carhart (1997) and Fama and French (1993) for a discussion. UK Data for these factors (including the UK risk free rate) is provided by Gregory et al. (2013). The portfolio holding period are respectively BULL 1 (July 1996 – August 2000), BEAR 1 (September 2000 – March 2003), BULL 2 (April 2003 – October 2007), BEAR 2 (November 2007 to June 2011). N (Months) represents the length of the holding period in months. The estimate of the intercept term 'Alpha' provides a test of the null hypothesis that the mean monthly excess return on the calendar-time portfolio is zero. ***, **, * indicate significance at 1%, 5% and 10%, respectively.

The results obtained using the decile portfolio selection strategy show that the portfolios generate average monthly excess returns (or alphas) of 3.4% (equal-weighted portfolio) and 2.8% (value-weighted portfolio) in BULL 1. These results are significant at the 1% level. The results are not replicated in BULL 2 as the alphas generated in this period are not statistically different from zero. The alpha's generated in BEAR 2 are significantly negative (–4.1% for the equal-weighted model and –2.7% for the value-weighted model).

The results obtained when alternative portfolio formation strategies (including quintiles, fixed portfolios and cut-offs) are employed are presented in table 7.2.3b. For simplicity, only the portfolio alphas generated from different factor models are presented. These results reinforce the suggestion that takeover prediction as investment strategy is potentially profitable in certain instances. The new model generates average alpha of 4.4% (equal-weighted portfolios) and 3.3% (value-weighted portfolios) in BULL 1. The model also generates positive but insignificant alpha in BEAR 1 (at the 10% level). The model generally performs poorly in BULL 2 as it generates an average alpha of – 0.8% (equal-weighted portfolios) and –0.6% (value-weighted portfolios) during this period. As expected the model performs very poorly in BEAR 2 – the global financial crises period – generating an average alpha of –5.9% (equal-weighted portfolios) and –3.4% (value-weighted portfolios) during this period.

In summary, the results show that employing the model during the 'dotcom bubble' – BULL 1 – would have generated significant abnormal returns to investors while employing the model during the 'global financial crisis' would have led to significant losses. The results highlight the level of variability and the likely inconsistency in the performance of the model. Overall, in the long run, the positive alphas generated in BULL1 appears to be neutralised by the negative alphas generated in BEAR 2 leading to an overall mediocre performance as reported in table 7.2.2a and 7.2.2b. These results suggest that even with perfect foresight of periods of market growth, an investor is unlikely to consistently generate positive risk-adjusted returns using the model (e.g., during BULL 2).

Table 7.2.3b: Carhart Alphas generated by the new model in bull and bear periods

Panel A: Equal Weighted portfolio returns				
	BULL 1	BEAR 1	BULL 2	BEAR 2
D10	0.034***	0.013*	-0.004	-0.041***
Q5	0.026***	0.013**	-0.002	-0.029***
Port100	0.036***	0.013	-0.004	-0.041***
Port50	0.049***	0.012	-0.006	-0.057***
Port30	0.063***	0.018	-0.010	-0.071***
Port10	0.088***	0.024	-0.021	-0.100***
CUT OFF	0.011**	0.012	-0.010	-0.090***
Port5%	0.048***	0.012	-0.006	-0.060***
Average	**0.044*****	**0.015*****	**-0.008*****	**-0.061*****
Median	**0.042**	**0.013**	**-0.006**	**-0.059**
Panel B: Value Weighted portfolio returns				
	BULL 1	BEAR 1	BULL 2	BEAR 2
D10	0.028***	0.009	-0.003	-0.027***
Q5	0.019***	0.010	-0.002	-0.017***
Port100	0.030***	0.005	-0.003	-0.028***
Port50	0.038***	0.007	-0.006	-0.033***
Port30	0.050***	0.023	-0.002	-0.045***
Port10	0.056***	0.057	-0.017	-0.070***
CUT OFF	0.008*	-0.001	-0.007	-0.084***
Port5%	0.037***	0.008	-0.005	-0.034***
Average	**0.033*****	**0.015*****	**-0.006*****	**-0.042*****
Median	**0.034**	**0.009**	**-0.004**	**-0.034**
N (Months)	50	31	55	44

Note: The table presents Carhart alphas obtained from cross sectional regression of portfolio returns on return-generation factors (Carhart model factors) when different portfolio formation strategies are employed. The regression model (eqn. 4.5.3(3)) is shown below:

$$(R_{it} - RF_t) = \alpha_i + \beta_{mkt}(RM_t - RF_t) + \gamma_{smb}SMB_t + \tau_{hml}HML_t + \rho_{umd}UMD_t + \varepsilon_{i,t}$$

The dependent variable is (R_{it} – RF_t) where R_{it} is the equal (panel A) or value (panel B) weighted return on the various portfolios (D10, Q5, Port100, Port50, Port30, Port10, Cut Off, Port5%) and RF_t is the risk free rate. The independent variables include the factors in the Carhart model; *RM - RF* (excess market return), *SMB* (size factor), *HML* (book to market factor) and *UMD* (momentum factor). See Carhart (1997) and Fama and French (1993) for a discussion. UK Data for these factors (including the UK risk free rate) is provided by Gregory et al. (2013). The portfolio holding period are respectively BULL 1 (July 1996 – August 2000), BEAR 1 (September 2000 – March 2003), BULL 2 (April 2003 – October 2007), BEAR 2 (November 2007 to June 2011). N (Months) represents the length of the holding period in months. The estimate of the intercept term 'Alpha' provides a test of the null hypothesis that the mean monthly excess return on the calendar-time portfolio is zero. ***, **, * indicate significance at 1%, 5% and 10%, respectively.

Powell (2004) can be used to provide some context to the results from this section. Powell (2004) reports returns to portfolios formed in January 1996 and held for a period of 12, 24 and 36 months. Powell (2004) shows that the binomial model achieves zero abnormal returns in the first 12 months (January 1996 – December 1996) and negative abnormal returns if the predicted target portfolio is held for 24 months (January 1996–December 1997) or 36 months (January 1996 – December 1998). This period coincides with periods of significant market growth – BULL 1. Notwithstanding, Powell (2004) notes that the model generates positive abnormal returns if the portfolio is limited to larger, more liquid, low leverage and better performing firms.

The new model appears to improve on Powell's model (Powell (2004)) as it leads to the generation of positive abnormal returns during BULL 1. Further, the results in this section suggest that studies (such as Palepu (1986), Barnes (1998, 1999, 2001) and Powell (2001, 2004)) which apply a short (usually one-year) holdout period to test model performance, potentially, report biased and non-generalisable results.

7.2.4 The new model versus the old model

The purpose of this section is to compare the performance of the old model with that of the new model in terms of their ability to generate abnormal returns. The results from section 7.2.2 showed that the new model generates mediocre abnormal returns over the long run.

Table 7.2.4 presents summary performance results for the old and new models. The old model attains lower levels of portfolio concentration but generate higher levels of alpha across corresponding portfolios. Similar to the new model, the alphas generated by the old model when equal-weighted portfolios are applied are generally insignificant. The old model outperforms the new model when value-weighted portfolios are applied as it is able to generate long run positive alphas of up to 3.3% in some instances (see, for example, Port30). Indeed, when compared to the new model, the old model performs well across several portfolios, achieving an average alpha of 1.8% per month over the test period. These results are inconsistent with the general premise of takeover prediction as a prediction strategy – investors can earn significant abnormal returns by investing in takeover targets. Further analysis on the old model's performance across different market states is done in section 7.3. The results here (table 7.2.4) show that the ability to predict more takeover targets successfully does not necessarily translate into better returns for shareholders. This is evident as the old model underperforms the new model in terms of predictive ability but outperforms the new model in terms of potential to generate abnormal returns for investors. Some of the potential reasons for this finding are further explored in section 7.3.

Table 7.2.4: Abnormal returns (alphas) generated by the new and old models

Panel A: Equal-Weighted Portfolios

	New Model		Old Model		Difference	
	Conc.%	Alpha	Conc.%	Alpha	Conc.%	Alpha
D10	10.47	0.003	8.37	0.008	2.10**	-0.005
Q5	9.96	0.003	7.93	0.005	2.03***	-0.002
Port100	10.40	0.004	8.13	0.010*	2.27**	-0.006
Port50	11.20	0.005	8.13	0.013	3.07***	-0.008
Port30	10.89	0.004	8.89	0.016	2.00	-0.012
Port10	9.33	0.004	8.00	0.017	1.33	-0.013
CUT OFF	8.12	-0.023***	9.19	0.001	-1.06	-0.024
Port5%	11.23	0.003	7.85	0.011	3.38***	-0.008
Average	**10.20*** **	**0.000**	**8.31*** **	**0.010*** **	**1.62*** **	**-0.010*** **
Median	**10.44**	**0.004**	**8.13**	**0.011**	**2.31**	**-0.007**

Panel B: Value-Weighted Portfolios

	New Model		Old Model		Difference	
	Conc.%	Alpha	Conc.%	Alpha	Conc.%	Alpha
D10	10.47	0.006*	8.37	0.012***	2.10**	-0.006
Q5	9.96	0.005*	7.93	0.009***	2.03***	-0.004
Port100	10.40	0.005	8.13	0.019***	2.27**	-0.014
Port50	11.20	0.008	8.13	0.025***	3.07***	-0.017
Port30	10.89	0.009	8.89	0.033***	2.00	-0.024
Port10	9.33	0.007	8.00	0.015	1.33	-0.008
CUT OFF	8.12	-0.023***	9.19	0.008**	-1.06	-0.031
Port5%	11.23	0.007	7.85	0.021***	3.38***	-0.014
Average	**10.20*** **	**0.003*** **	**8.31*** **	**0.018*** **	**1.62*** **	**-0.018*** **
Median	**10.44**	**0.007**	**8.13**	**0.017**	**2.31**	**-0.011**

Note: The table presents alphas (constant term and significance) for cross sectional regression of portfolio returns on return-generation factors (CAPM, Fama and French three Factor and Carhart model factors) for different portfolio formation strategies. The regression model (eqn. 4.5.3(3)) is shown below:

$$(R_{it} - RF_t) = \alpha_i + \beta_{mkt}(RM_t - RF_t) + \gamma_{smb}SMB_t + \tau_{hml}HML_t + \rho_{umd}UMD_t + \varepsilon_{i,t}$$

The dependent variable is $(R_{it} - RF_t)$ where R_{it} is the equal (panel A) or value (panel B) weighted return on the various portfolios (D10, Q5, Port100, Port50, Port30, Port10, Cut Off, Port5%) and RF_t is the risk free rate. The independent variables include the factors in the Carhart model; *RM - RF* (excess market return), *SMB* (size factor), *HML* (book to market factor) and *UMD* (momentum factor). See Carhart (1997) and Fama and French (1993) for a discussion. UK Data for these factors (including the UK risk free rate) is provided by Gregory et al. (2013). The portfolio holding period is 180 months from July 1996 to June 2011. Conc. % represents the proportion of actual takeover targets within the portfolio. The estimate of the intercept term 'Alpha' provides a test of the null hypothesis that the mean monthly excess return on the calendar-time portfolio is zero. ***, **, * indicate significance at 1%, 5% and 10%, respectively.

This section has explored the performance of the new model in the long run and across different sub-periods. The results show that the model performs well in some periods (e.g., BULL 1) but also performs poorly in other periods (e.g., BEAR 2). Overall, in the long run (over the 180 months period), the model generates positive abnormal returns only when the value-weighted portfolios are employed together with decile or quintile selection portfolio strategy. Given that transaction costs have not been considered, the abnormal returns are at best mediocre as they range from only 0.5% to 0.6% per month[186].

In section 7.2.4, I compare the performance of the new model with the performance of the old model. The results reveal that even though the new model outperforms the old model in terms of predicting actual targets, it underperforms the old model in terms of its ability to generate returns for investors. The finding suggests that, in the case of takeover prediction as an investment strategy, high predictive ability does not necessarily translate to high returns to investors. In section 7.3, I conduct several tests to explore some reasons why the new model underperforms the old model. I also explore possible factors that moderate the returns to target portfolios.

7.3 Factors that influence the magnitude of portfolio returns

7.3.1 Overview

The results from chapter 6 suggest that the new variables considerably improve the predictive ability of the old takeover prediction model. The focus of this chapter was to test whether takeover prediction models (such as the new model) can, potentially, generate abnormal returns for investors in the long run. The results in section 7.2 suggest that an investment strategy relying on the prediction of takeover targets is unlikely to consistently generate significant positive returns in the long term. These results from the new model are consistent with the Efficient Market Hypothesis (EMH) and corroborate prior empirical studies (such as Palepu (1986), Barnes (1998, 1999, 2000), Powell (2001, 2004) and Cahan et al. (2011)). The results from the old model are consistent with the results of studies by Brar et al. (2009) and Cremers et al. (2009) who argue that abnormal returns can be generated from prediction models – albeit without sufficiently robust empirical evidence as critiqued earlier.

It is interesting to take these findings a step further by empirically investigating why the new model's portfolios underperform, on average, despite their higher target concentrations (as established in chapter 6). While some seminal studies have concluded

186 Several studies have derived trading strategies that yield much higher returns. For example, Diether et al. (2009) show that a trading strategy that buys stocks with low short-selling activity and sells short stocks with high short-selling activity generates an abnormal return of roughly 1.39% (1.41%) per month for NYSE (Nasdaq) stocks.

that takeover prediction (and therefore benefiting from it) is in fact difficult, their conclusions are attributed to the fact that their models reported low predictive abilities (further discussed in section 2.5). Here, I show that the new model which attains a comparatively higher target concentration underperforms the old model, suggesting that target concentration is not a prerequisite for achieving high abnormal returns. In sections 7.3.2, 7.3.3 and 7.3.4, I investigate the roles of type II errors (predicted targets which do not receive takeover bids), bankrupt firms and small firms in prediction portfolios. The key question here is whether the concentration of these categories of firms explains the poor performance of the new model and the differences in performance between the new and old models. In section 7.3.5, I explore whether the inability to generate high returns can be explained by the contention that stock prices already reflect takeover probability – market efficiency.

7.3.2 The effect of type II errors

Studies in takeover prediction (e.g., Palepu (1986), Barnes (1998, 1999, 2000), Powell (2001, 2004) and Cahan et al. (2011), amongst others) frequently argue that the presence of poorly performing non-targets in the prediction portfolio (i.e., predicted targets which do not receive a bid or type II errors) explains why prediction portfolios generate mediocre returns. The suggestion is that these type II errors (i.e., non-targets with a target's profile) are strategically better-off if acquired by another firm. The expectation, therefore, is that such firms are likely to continue to perform poorly unless acquired by a new management team. If this is the case, the presence of type II errors in the target portfolio will explain a substantial portion of the low returns to these portfolios.

I conjecture that while targets perform well, non-targets in portfolios (type II errors) perform poorly, thus dragging down the overall performance of portfolios. I investigate whether type II errors (predicted targets which do not receive bids) underperform other non-targets and whether portfolios without type II errors (100% target concentration) earn significant abnormal returns. To investigate this proposition (underperformance of type II errors), I compare the performance of non-targets in the predicted targets portfolio (Q5) with the performance of non-targets in Q1 (portfolio of firms with lowest acquisition likelihood). If the proposition is valid, I expect a significant difference in performance between non-targets in Q5 and non-targets in Q1, with Q5 non-targets underperforming[187].

[187] Bankrupt/delisted firms are also excluded from the non-target subsamples to ensure that their extreme performance does not bias the results as the intention is solely to investigate how the average non-target performs. The performance of bankrupt firms is investigated in section 7.3.3.

Second, I also expect that abnormal returns will be earned if the model was perfect (achieving a 100% target concentration). To investigate this, I compute the returns earned by a portfolio of targets only. Finally, I compare the results for the new model with those for the old model. My focus is to evaluate whether difference in the abnormal returns to targets and non-targets selected by the two models explain the differences in performance. The results of the analysis are summarised in table 7.3.2.

The portfolio of predicted targets in Q5 (consisting of actual targets and non-targets) generates an alpha of 0.30% and 0.50% (insignificant at the 10% level) for the new and old models, respectively. When all the actual targets are taken-off the portfolio, the portfolio alpha does not change (i.e., the non-targets only portfolio alpha equals 0.30% and 0.50% for the new and old models, respectively). The alpha earned by the target-only portfolio (i.e., portfolio made up of only the actual targets in Q5) is slightly higher (0.50%) for the new model but still insignificant. Interestingly, the results suggest that a perfect (new or old) model – which generates small[188] portfolios with 100% target concentration – fails to generate a significant positive alpha over the period.

These results support the contention that the ability to successfully predict takeover targets does not imply superior investment performance. These results are consistent with Cremers et al. (2009) who find that the presence of targets within predicted target portfolios do not explain the returns to these portfolios. In their study, Cremers et al. (2009) find that portfolio alpha does not change when actual targets are excluded from these portfolios. They write: 'To shed light on the source of these abnormal returns, we remove from our samples all firms that were actual targets, and recompute abnormal returns accruing to the different portfolios. Our results remain consistent and of (an arguably surprisingly) similar magnitude. Therefore, these abnormal returns are not caused by the announcement returns to realised targets' (Cremers et al. (2009), p. 1424, footnote 19). The results mirror their finding and partly explain why the new model underperforms the old model (in terms of generating abnormal returns) even though it achieves a substantially higher target concentration.

[188] The portfolios analysed here are obtained by taking out all the non-targets from Q5.

Table 7.3.2: The effects of type II errors on portfolio returns

		All Q5	All Q1	NT Q5	Targets Q5	NT Q1	Targets Q1
Panel A: Full-period analysis - New model							
	Alpha	0.003	-0.005	0.003	0.005	-0.008***	-0.005
	RM - RF	0.860***	0.732***	0.872***	0.106***	0.817***	0.732***
	SMB	1.108***	0.495**	1.129***	0.126***	0.653***	0.495**
	HML	0.101	-0.580**	0.081	0.364***	-0.186**	-0.580**
	UMD	0.062	-0.244	0.068	0.017	-0.153*	-0.244
Panel B: Full-period analysis - Old model							
		All Q5	All Q1	NT Q5	Targets Q5	NT Q1	Targets Q1
	Alpha	0.005	-0.003	0.005	0.000	-0.003	0.008
	RM - RF	0.892***	0.839***	0.902***	0.884***	0.839***	0.806***
	SMB	1.123***	0.739***	1.146***	0.841***	0.739***	0.621***
	HML	0.037	-0.199*	-0.013	0.580***	-0.199*	0.070
	UMD	0.124	-0.263***	0.127	0.205*	-0.263***	0.166
Panel C: Sub-period analysis - New model							
		All Q5	All Q1	NT Q5	Targets Q5	NT Q1	Targets Q1
BULL 1	Alpha	0.026***	-0.007	0.025***	0.039***	-0.022***	-0.007
BEAR 1	Alpha	0.013**	-0.073*	0.013**	0.019	-0.026***	-0.073*
BULL 2	Alpha	-0.002	0.004	-0.002	-0.001	0.000	0.004
BEAR 2	Alpha	-0.028***	0.018	-0.029***	-0.035***	0.022***	0.018
Panel D: Sub-period analysis - Old model							
		All Q5	All Q1	NT Q5	Targets Q5	NT Q1	Targets Q1
BULL 1	Alpha	0.030***	-0.021***	0.029***	0.038***	-0.021***	-0.011
BEAR 1	Alpha	0.016**	-0.034***	0.017**	0.001	-0.034***	-0.045*
BULL 2	Alpha	0.000	0.001	0.000	0.005	0.001	0.003
BEAR 2	Alpha	-0.032***	0.043***	-0.031***	-0.053***	0.043***	0.083***

Notes: The table presents results for cross sectional regression of portfolio returns on return-generation factors (CAPM, Fama and French three Factor and Carhart model factors). The regression model (eqn. 4.5.3(3)) is shown below:

$$(R_{it} - RF_t) = \alpha_i + \beta_{mkt}(RM_t - RF_t) + \gamma_{smb}SMB_t + \tau_{hml}HML_t + \rho_{umd}UMD_t + \varepsilon_{i,t}$$

The dependent variable is $(R_{it} - RF_t)$ where R_{it} is the equal weighted return on the various portfolios (All Q5, NT Q5, targets Q5, NT Q1 and Targets Q1) and RF_t is the risk free rate. All Q5 is a portfolio consisting of 20% of firms with the highest takeover likelihood in each year (predicted targets). NT Q5 (non-targets Q5) is a subset of All Q5 consisting of a portfolio of all predicted targets which do not receive a takeover bid (type II errors). Targets Q5 is a subset of All Q5 consisting of a portfolio of predicted targets which receive a bid as predicted. NT Q1 (Targets Q1) is a portfolio of non-targets (actual targets) in quintile 1 (quintile of firms with least likelihood of receiving a takeover bid. The independent variables in the model include the factors in the Carhart model; *RM - RF* (excess market return), *SMB* (size factor), *HML* (book to market factor) and *UMD* (momentum factor). See Carhart (1997) and Fama and French (1993) for a discussion. UK Data for these factors (including the UK risk free rate) is provided by Gregory et al. (2013). The portfolio holding period in panels A and B is 180 months from July 1996 to June 2011. The portfolio holding periods in panels C and D are respectively BULL 1 (July 1996 – August 2000), BEAR 1 (September 2000 – March 2003), BULL 2 (April 2003 – October 2007), BEAR 2 (November 2007 to June 2011).The estimate of the intercept term 'Alpha' provides a test of the null hypothesis that the mean monthly excess return on the calendar-time portfolio is zero. Panel A presents results for the full period. Panel B presents results for different sub periods. ***, **, * indicate significance at 1%, 5% and 10%, respectively.

One potential reason for the underperformance of target-only portfolios (Targets Q5) is that their returns (even if high) are explained by the risk factors in the four factor model. To further explore why target-only portfolios underperform, I look at the raw returns to these portfolios. For the new model (for example), I find that the target-only portfolio generates a buy-and-hold and an average monthly return of 530% and 1.342%, respectively between July 1996 and June 2011. That is, £1 invested in the portfolio in July 1996 would have grown to £5.30 by June 2011. During the same period, the market (FTSE All Share index) achieved a buy-and-hold and an average monthly return of 168% and 0.641%, respectively. Clearly, the target-only portfolio outperforms the market portfolio. The low return to the target-only portfolio (for the new and old models) appears to be explained by the high loading on the HML factor in the factor model (see, table 7.3.2). The coefficient of the HML factor when the entire portfolio (All Q5) is considered is 0.101 (new model, panel A) and 0.037 (old model, panel B) insignificant at the 10% level. When only targets are considered (Targets Q5), the coefficient of the HML factor changes to 0.364 (new model) and 0.580 (old model), significant at the 1% level. This suggests that the returns to target (Target Q5) are mainly explained by the 'value premium' captured by the HML risk factor in the factor model[189].

Contrary to the suggestions of prior researchers (e.g., Cahan et al. (2011)), non-targets in Q1 appear to underperform the non-targets in Q5. That is non-targets with a low takeover likelihood underperform non-targets with a high takeover likelihood. This is especially the case with the new model. This finding is inconsistent with the argument that predicted target portfolios underperform due to the exceptionally poor performance of type II errors. Cahan et al. (2011) argue that predicted target portfolios underperform due to the presence of non-targets (type II errors) – potential targets which do not receive takeover bids. The findings here show that type II errors do not (comparatively) underperform other non-targets as suggested by Cahan et al. (2011).

[189] The value premium is the attributed to the tendency for value-stocks to outperform growth stocks. The conclusions here do not change when the CAPM is applied.

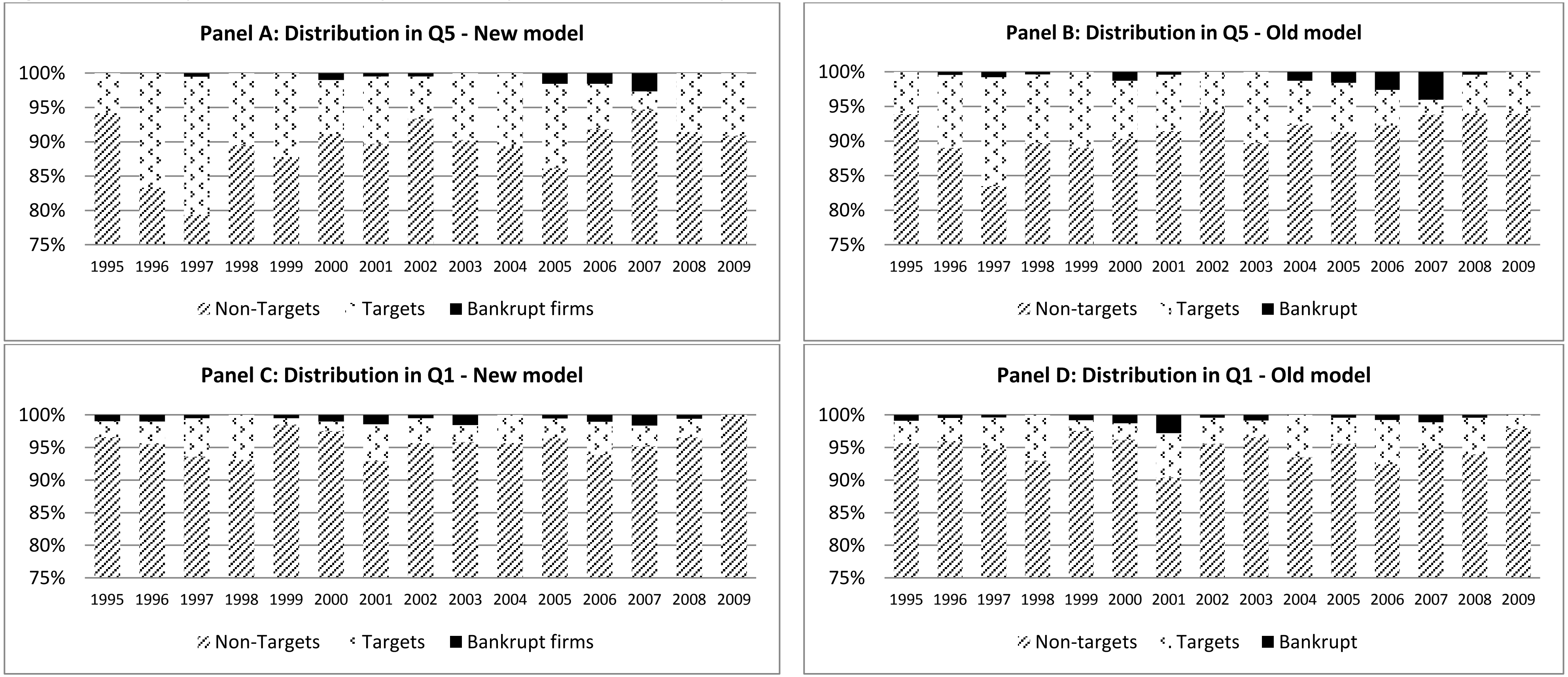
7.3.3 The effect of bankrupt firms

Empirical research by Powell and Yawson (2007) has shown that targets and bankrupt firms share certain characteristics. The implication is that predicted target portfolios are likely to have a substantial number of potential candidates for bankruptcy, liquidation, or delisting. The presence of such firms in a prediction portfolio is substantially detrimental as they can lead to a 100% loss of investment. To my knowledge, no prior study has taken this issue into consideration. The use of a matched-sample methodology in some studies (such as Palepu et al. (1986), Brar et al (2009) and Cahan et al. (2011)) not only generates survival bias in the analysis but also underestimates the effect of bankrupt firms in takeover prediction portfolios.

The use of a pooled population sample in this study guards against survival bias. Further, to factor in the effect of bankruptcy on portfolio returns, a return of –100% is ascribed to each delisted/bankrupt firm in the month in which it is delisted. This is bound to have a negative effect on portfolio returns, if prediction portfolios contain a substantial number of bankrupt firms as suggested by Powell and Yawson (2007). Unlike the old model, the new model attempts to control for the risk of bankruptcy (financial distress hypothesis) using Taffler Z Scores. This is discussed in sections 3.3.4 and 5.3.4. The expectation is that new model portfolios will, perhaps, have fewer bankrupt firms when compared to old model portfolios. Therefore, the differences in concentration of bankrupt firms between the two models' portfolios (if such differences exist) are unlikely to explain the differences in abnormal returns to these portfolios as the old model outperforms the new model. Nonetheless, the returns to the portfolios are likely to be higher if bankrupt firms are excluded (or not considered) in the analysis. The effect of excluding bankrupt firms is also likely to be more significant for the old model.

Figure 7.3.3 shows the distribution of targets, non-targets and bankrupt firms in the new and old models' predicted target portfolios (Q5) and non-target portfolios (Q1) between 2000 and 2009.

Figure 7.3.3: Proportion of bankrupt firms in quintile 5 (Q5) and quintile 1 (Q1)



Notes: Panels A to D show the distribution of non-targets, targets and bankrupt firms in Q5 and Q1 for the old and new models. Q5 (Q1) is the quintile of firms with the highest (lowest) takeover likelihood. The axis in panels A to D starts at 75% to improve visibility and allow for cross-comparison. For the New model, Q5 is composed of 89.51% non-targets, 9.96% targets and 0.54% bankrupt firms. Q1 is composed of 94.74% non-targets, 3.52% targets and 0.74% bankrupt firms. For the old model, Q5 is composed on 91.23% non-targets, 7.86% targets and 0.91% bankrupt firms. Q1 is composed on 94.87% non-targets, 4.42% targets and 0.70% bankrupt firms.

As expected, Q5 has more targets and fewer non-targets than Q1 in every year (2000–2009). The number of bankrupt firms in Q1 (22 for the new model and 34 for the old model) is slightly higher than the number of bankrupt firms in Q1 (16 for the new model and 26 for the old model) over the period. The old model has a higher number of bankrupt firms in its predicted target portfolio (Q5). The proportion of bankrupt firms in Q1 and Q5 is higher at the onset of bear periods (dotcom crises: 2000 and 2001 and global financial crisis: 2007). This is, perhaps, because many more firms are likely to fail during market downturns. Bankrupt firms in target portfolios, perhaps, contribute towards the poor performance of these portfolios. The effect is likely to be higher for the old model given the higher number of bankrupt firms in its target portfolio. To test the effect of bankrupt firms on the results obtained, I exclude bankrupt firms from the portfolios and recompute the equal-weighted portfolio returns. The results are presented in table 7.3.3.

Table 7.3.3: The effect of bankrupt firms on portfolio returns

Panel A: Full-period analysis

		New model		Old model	
		All Q5	Q5 (WB)	All Q5	Q5 (WB)
	Alpha	0.003	0.004	0.005	0.007*
	RM - RF	0.860***	0.860***	0.892***	0.886***
	SMB	1.108***	1.113***	1.123***	1.116***
	HML	0.101	0.106	0.037	0.024
	UMD	0.062	0.059	0.124	0.113

Panel B: Sub-period analysis

		New model		Old model	
		All Q5	Q5 (WB)	All Q5	Q5 (WB)
BULL 1	Alpha	0.026***	0.027***	0.030***	0.031***
BEAR 1	Alpha	0.013**	0.015**	0.016**	0.017**
BULL 2	Alpha	-0.002	-0.001	0.000	0.002
BEAR 2	Alpha	-0.028***	-0.028***	-0.032***	-0.028***

Notes: The table presents results for cross sectional regression of equal-weighted portfolio returns on return-generation factors (CAPM, Fama and French three Factor and Carhart model factors). The regression model (eqn. 4.5.3(3)) is shown below:

$$(R_{it} - RF_t) = \alpha_i + \beta_{mkt}(RM_t - RF_t) + \gamma_{smb}SMB_t + \tau_{hml}HML_t + \rho_{umd}UMD_t + \varepsilon_{i,t}$$

The dependent variable is (R_{it} – RF_t) where R_{it} is the equal weighted return on the various portfolios (All Q5, Q5(WB)) and RF_t is the risk free rate. All Q5 is a portfolio consisting of 20% of firms with the highest takeover likelihood in each year (predicted targets). Q5 (WB) is All Q5 without bankrupt firms. The independent variables in the model include the factors in the Carhart model; *RM - RF* (excess market return), *SMB* (size factor), *HML* (book to market factor) and *UMD* (momentum factor). See Carhart (1997) and Fama and French (1993) for a discussion. UK Data for these factors (including the UK risk free rate) is provided by Gregory et al. (2013). The portfolio holding period in panels A and B is 180 months from July 1996 to June 2011. The portfolio holding periods in panels C and D are respectively BULL 1 (July 1996 – August 2000), BEAR 1 (September 2000 – March 2003), BULL 2 (April 2003 – October 2007), BEAR 2 (November 2007 to June 2011). The estimate of the intercept term 'Alpha' provides a test of the null hypothesis that the mean monthly excess return on the calendar-time portfolio is zero. Panel A presents results for the full period. Panel B presents results for different sub periods. ***, **, * indicate significance at 1%, 5% and 10%, respectively.

The results show that the returns to target portfolios improve if bankrupt firms are excluded from the portfolios. In the case of the new model, the return to the portfolio remains insignificant (panel A). The alpha earned by Q5 increases from 0.30% to 0.40%. In the case of the old model, the return to Q5 increases from 0.5% (insignificant) to 0.7% (significant at the 10% level). As shown in figure 7.3.3, the old model generates portfolios with a higher number of bankrupt firms than the new model[190]. This partly explains why the exclusion of bankrupt firms has a more profound effect on target portfolios generated by the old model. Sub-period analysis also reveals an increase in performance when bankrupt firms are excluded from the sample. Overall, the results suggest that the presence of bankrupt firms within predicted target portfolios reduces the abnormal returns earned by the portfolios. This effect is more substantial for the old than the new model.

7.3.4 The effect of small firms

Prior empirical research has suggested that, on average, small firms are likely to be non-liquid (and hence not readily tradable), highly risky (e.g., bankruptcy risk) and more likely to be underperforming when compared to their large counterparts (see, for example, Mansfield (1962), Singh and Whittington (1975), Chan and Chen (1991), Fama and French (1995, 1996), Gompers and Metrick (2001), Yang and Chen (2009) and van Dijk (2011), amongst others). Some prior takeover prediction studies (such as Brar et al. (2009)) restrict their samples to large firms with market capitalisation of $100 million or greater. Taking out small firms from an investment portfolio might be justified on the grounds of liquidity problems which are exacerbated by small firms with stocks that are not easily tradable. It can also be expected that investors in practice will impose some qualitative criteria on their investments which amongst others can be the restriction of investment to firms above a certain minimum size.

Evidence from Morgan Stanley Target Equity Index (2003–2011) and Cahan et al. (2011), for example, shows that Morgan Stanley IQ and Deutsche Bank potentially employ a qualitative screening procedure in addition to the quantitative based predictions in their investment decision making. Gompers and Metrick (2001) also find that institutional investors show a preference for larger stocks over small stocks. The results from section 7.2 revealed notable differences between returns to equal-weighted and value-weighted

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190 This is, perhaps, because the new model attempts to control for the incidence of bankruptcy through the inclusion of financial distress variables (Taffler Z Score and Z Score dummy).

portfolios. It is probable that the presence of many small firms within prediction portfolios drags down the returns of predicted target portfolios.

As discussed in sections 3.2.8, 3.3.2, 5.2.8 and 5.3.2, the old and new models treat firm size differently (linear and inverted U-shaped relationship with takeover likelihood, respectively). The coefficients of the models indicate that the old model attributes higher takeover likelihood to large firms (positive relationship) while the new model attributes higher takeover likelihood to medium-size firms (inverted U-shaped relationship. This suggests that the firms in the new model's portfolios are on average smaller than those in the old model's portfolios. Indeed, this is the case. The average market capitalisations of the new and old models' portfolios over the period 1995 to 2009 are £304 million and £1,803 million, respectively. The old model's portfolios are made up of significantly larger firms and the average market capitalisations of the firms in portfolios are comparatively higher in each year. The results in table 7.2.4 show that, when equal and value-weighted portfolios are considered, the old model outperforms the new model across several portfolios. The difference is more significant for value-weighted portfolios.

In this section, I investigate whether the presence of a significant number of small firms in the portfolios partly accounts for the underperformance of the new model and whether the returns to the old model's target portfolios can be further improved by investing in the largest firms only. To investigate these issues, firms with market values below three thresholds of (1) £50 million (2) £100 million and (3) £500 million are excluded from the analysis (in succession) and alphas generated by the screened portfolios are recomputed. This size control is in addition to the SMB (small minus big) factor already included in the alpha generation model. The results are shown in table 7.3.4.

Table 7.3.4: The effect of small firms on portfolio returns

		All Q5	Q5 Large: 50M	Q5 Large: 100M	Q5 Large: 500M
Panel A: Full-period analysis - New model					
	Alpha	0.003	0.003	0.004*	0.004
	RM - RF	0.860***	0.899***	0.907***	0.956***
	SMB	1.108***	1.011***	0.059***	0.741***
	HML	0.101	0.186***	0.135**	0.027
	UMD	0.062	0.018	-0.023	-0.075
Panel B: Full-period analysis - Old model					
		All Q5	Q5 Large: 50M	Q5 Large: 100M	Q5 Large: 500M
	Alpha	0.005	0.006**	0.007***	0.008***
	RM - RF	0.892***	0.969***	0.982***	0.960***
	SMB	1.123***	0.932***	0.841***	0.555***
	HML	0.037	0.075	0.033	0.042
	UMD	0.124	0.025	0.000	-0.016
Panel C: Sub-period analysis - New model					
		All Q5	Q5 Large: 50M	Q5 Large: 100M	Q5 Large: 500M
BULL 1	Alpha	0.026***	0.019***	0.017***	0.018***
BEAR 1	Alpha	0.013**	0.011	0.011	0.014
BULL 2	Alpha	-0.002	-0.003	-0.001	-0.004
BEAR 2	Alpha	-0.028***	-0.018***	-0.015***	-0.017***
Panel D: Sub-period analysis - Old model					
		All Q5	Q5 Large: 50M	Q5 Large: 100M	Q5 Large: 500M
BULL 1	Alpha	0.030***	0.022***	0.021***	0.019***
BEAR 1	Alpha	0.016**	0.015**	0.015*	0.014*
BULL 2	Alpha	0.000	-0.002	0.001	0.002
BEAR 2	Alpha	-0.032***	-0.017***	-0.012***	-0.008**

Notes: The table presents results for cross sectional regression of equal-weighted portfolio returns on return-generation factors (CAPM, Fama and French three Factor and Carhart model factors).). The regression model (eqn. 4.5.3(3)) is shown below:

$$(R_{it} - RF_t) = \alpha_i + \beta_{mkt}(RM_t - RF_t) + \gamma_{smb}SMB_t + \tau_{hml}HML_t + \rho_{umd}UMD_t + \varepsilon_{i,t}$$

The dependent variable is (R_{it} – RF_t) where R_{it} is the equal weighted return on the various portfolios (All Q5, Q5 Large: 50M, Q5 Large: 100M and Q5 Large: 500M) and RF_t is the risk free rate. All Q5 is a portfolio consisting of 20% of firms with the highest takeover likelihood in each year (predicted targets). Q5 Large: 50M (100M and 500M) is similar to ALL Q5 but excludes firms with a market capitalisation of less than £50million, £100million and £500million, respectively. Market capitalisation is computed at the start of the holding period (i.e., using June 30th closing prices). The independent variables in the model include the factors in the Carhart model; *RM - RF* (excess market return), *SMB* (size factor), *HML* (book to market factor) and *UMD* (momentum factor). See Carhart (1997) and Fama and French (1993) for a discussion. UK Data for these factors (including the UK risk free rate) is provided by Gregory et al. (2013). The portfolio holding period in panels A and B is 180 months from July 1996 to June 2011. The portfolio holding periods in panels C and D are respectively BULL 1 (July 1996 – August 2000), BEAR 1 (September 2000 – March 2003), BULL 2 (April 2003 – October 2007), BEAR 2 (November 2007 to June 2011).The estimate of the intercept term 'Alpha' provides a test of the null hypothesis that the mean monthly excess return on the calendar-time portfolio is zero. ***, **, * indicate significance at 1%, 5% and 10%, respectively.

The results from table 7.3.4 show that the exclusion of firms with market value below £50 (£100 and £500) million from the predicted target portfolios (Q5) generally improves its long run performance. For the new model, the exclusion of firms with market value below £100 million results in an improvement of its alpha from 0.30% (insignificant at 10% level) to 0.40% (significant at 10% level). This indicates that the imposition of a size restriction of at least £100 million on predicted targets leads to the generation of significant abnormal returns from prediction modelling (using the new model). The performance of the portfolio is, however, not further improved when firms with market value below £500 million are excluded. In the case of the old model, the performance of the portfolio increases by 0.1 percentage point as the different size restrictions (£50 million, £100 million and £500 million) are successively imposed. The use of size restrictions has no discernable impact on returns generated in the different sub-periods. Overall, the results show that the presence of small firms within predicted target portfolios has a negative impact on the returns of the portfolios. The exclusion of small firms from the new model portfolios lead to the generation of significant abnormal returns (albeit, these returns are still lower than those generated by the old model).

7.3.5 The effect of potential market-wide bid anticipation

I conjecture that the models predict targets which can be predicted by other market participants – implying that their stock prices already partly reflect takeover probabilities. This is consistent with studies which argue that market anticipation partly explains the run-up in target prices prior to the announcement of takeover bids (see for example, Franks et al. (1977), Jensen and Ruback (1983), Jarrell and Poulsen (1989) and Pound (1990)). Assuming that the new model sums up the market's belief about the takeover likelihood of different firms, one could argue that actual target firms in D1 and Q1 (i.e., firms with low takeover probability that actually receive a bid), will be a surprise to the market. In such a case, I would expect the targets in Q1 and D1 to earn significantly higher returns than targets in D10 and Q5, with the difference in return between the two groups attributable to the surprise element.

The proposition is grounded in the market anticipation hypothesis and the EMH. It contends that targets which are 'predictable'[191] will earn lower returns compared to targets

[191] 'Predictable' here refers to highly anticipated takeover targets.

which are 'less predictable', as the market discounts takeover probabilities in share prices. If the new model, to an extent, reflects the market's perspective on likely takeover targets, then correctly predicted targets will earn lower returns. Hence, predicted target portfolios will generate low returns. Prior research has suggested that takeovers are highly anticipated events (Pound and Zeckhauser (1990)). The potential to generate windfall gains from this event is a motivation for investors to try to anticipate potential takeover bid announcements. The literature review (section 2.5.5) also highlighted the use of takeover prediction models in practice. Based on the EMH, it is likely that share prices reflect the market's belief of a firm's takeover probability. Under this framework, the market reaction on the announcement day is a revision of the market's assessment of the firm's likelihood of receiving a takeover bid. I demonstrate this as follows.

For example, consider a firm *i,* and two mutually-exclusive and collectively-exhaustive states: B ('bid') and N ('no bid'), in period *T*. The probability of state B occurring is given by P_B and the probability of state N occurring is given as, $1 - P_B$. The price per share of firm *i* today (T_0) is equal to λ. In state N, the price per share of firm *i*, is given by λ_N. In state B, the price per share of *i,* is given by λ_B. λ_B is a function of λ_N as (λ_B-λ_N)/ λ_N is the bid announcement premium α (α > 0). This implies that λ_B = (1+ α) λ_N . If the market is efficient, the price of the stock, at every point in time, will reflect the market's anticipation of the likelihood of receiving a bid and can be modelled as follows.

$$Price = (1 - P_B)\lambda_N + P_B\,\lambda_B \ldots\ldots\ldots Eqn\ 7.3.4(1)$$

If the market receives no new information for firm *i* between T_0 and *T* (exclusive), then;

$$\lambda = \lambda_N \implies Price = \lambda(1 + \alpha P_B) \ldots\ldots\ldots Eqn 7.3.4(2)$$

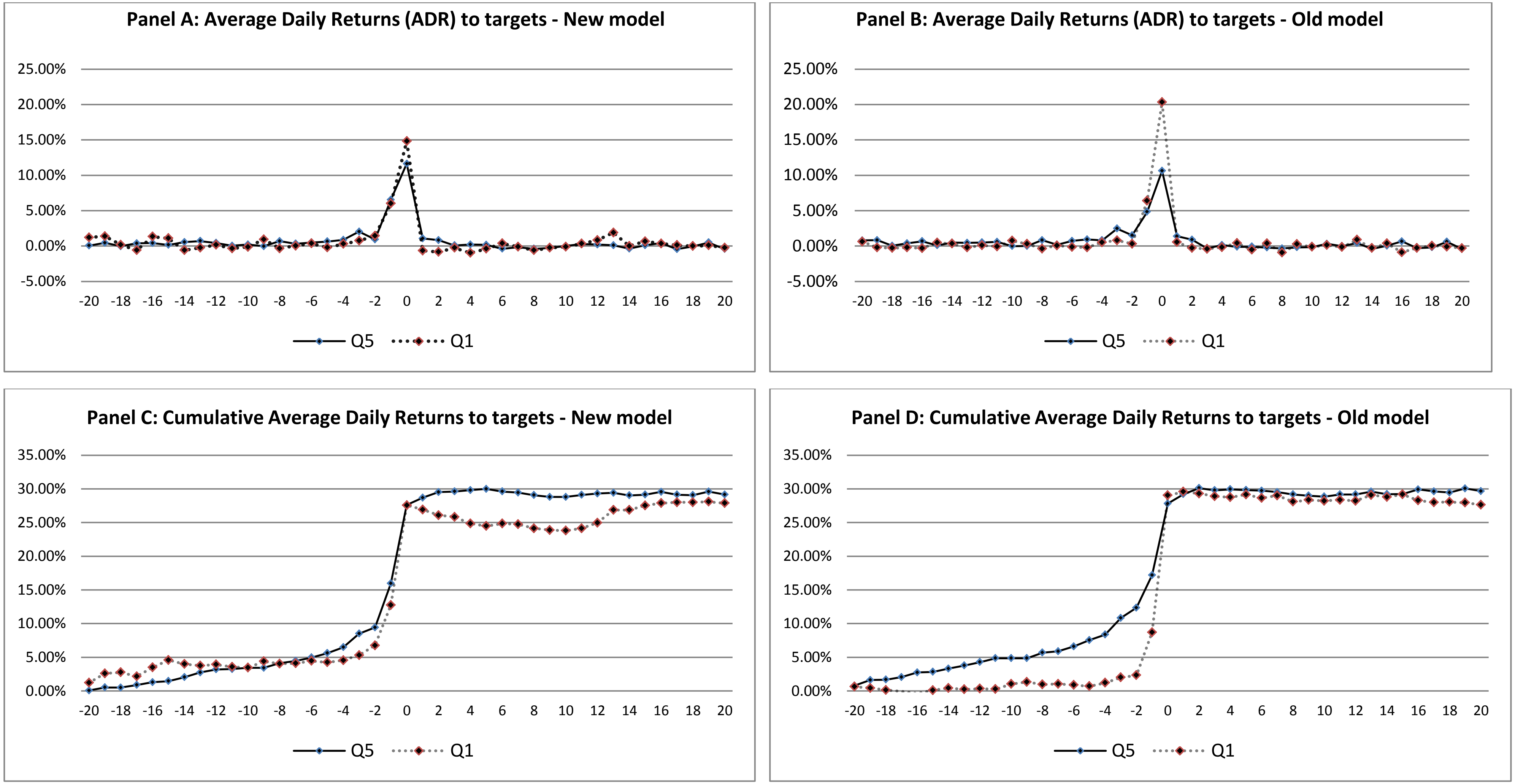
Therefore, in an efficient market, the price of the stock at point *T*, other things being equal, is a function of its current price (λ), the probability that it will receive a takeover bid (P_B) and the expected bid premium (α).

Suppose the expected bid premium, α is 25% (0.25). If the market believes firm *i*, has a 20% chance of receiving a bid (scenario 1 – low takeover probability, $P_B = 0.2$), then its price today (T_0) will be 1.05 λ. That is, in an efficient market, its price will increase by 5% to reflect the 20% likelihood of a price increase of 25% at time *T*. If the market believes that the firm has an 80% chance of receiving a takeover bid at *T* (scenario 2 – high takeover probability, $P_B = 0.8$), then its price at T_0 will be 1.20 λ – i.e., a 20% increase in share price to reflect the probability of a 25% price increase at *T*. If the firm receives a bid in period *T*, then its price will be 1.25 λ, otherwise its price will be λ. Under scenario 1, the market reaction (or announcement return) at time T will be ([1.25 λ – 1.05 λ] / 1.05 λ = 0.1904) representing a 19.04% bid announcement return. Under scenario 2, the market reaction at time T will be ([1.25 λ – 1.20 λ] / 1.20 λ = 0.0416) representing a 4.16% bid announcement return. This simplistic framework shows that, all things being equal, larger announcement gains are likely to accrue to 'surprise' targets as compared to highly anticipated targets.

The implication of this analysis is that the market reaction to takeover announcements for 'predictable' targets will be lower than the market reaction for 'less-predictable' targets. Assuming that to some extent, the takeover prediction model sums up the market's belief about the takeover likelihood of different firms, one could argue that actual target firms in Q1 (i.e., firms with low takeover probability that actually receive a bid) will, on average, earn a higher return from mergers than their counterparts in Q5 (i.e., firms with high takeover probability that actually receive a bid). This suggestion of a 'market surprise premium' to targets with lower takeover probabilities complements Cornett et al. (2011). Cornett et al. (2011) finds that part of the large difference in announcement returns to targets and bidders in takeovers is due to the fact that bidders are more easily predicted than targets. Hence, the likelihood of becoming a bidder (but not a target) is factored into the share prices of firms long before the event date. The implication for investing in portfolios of predicted targets is that predicted target portfolios might earn lower than expected returns over the holding period partly because the market price of targets in these portfolios already reflect their high takeover probability.

I test this conjecture – the existence of a limited market surprise – by comparing the announcement returns to targets in Q1 and Q5. I focus on a short time period (day –20 to day 20 surrounding the bid. A significant positive difference between the returns to targets in Q1 and Q5 will, perhaps, indicate the existence of a 'market surprise premium'. This premium should, perhaps, be greater for the old model when compared to the new model. That is, firms in Q5 should constitute more of a market surprise for the old model when compared to the new model. This is because, unlike the old model, the new model utilises variables such as merger rumours, share repurchases, market liquidity, industry concentration and market economics which have been shown to be key drivers or determinants of M&A activity. Figure 7.3.5 plots the average and cumulative daily portfolio returns to targets in Q1 and Q5 for the new and old models.

Figure 7.3.5: Daily returns to targets in Q1 and Q5 – Old and New models



Notes: Figure 7.3.5 tracks the simple and cumulative returns to targets in quintile 1 (Q1) and quintile 5 (Q5) around the merger announcement day. The purpose of this analysis is simply to capture market reaction to the takeover bids for different targets. For simplicity, the reported returns are not adjusted for market risk. While this might impact on the results, the impact is, perhaps, low as the study period is the 40 days surrounding the bid. Q1 (Q5) represents the 20% of firms with the lowest (highest) takeover probability as prescribed by the old and new models. Only actual targets within these portfolios (Q1 and Q5) are used in the analysis. Panel A and C compare the average daily returns for targets in Q1 and targets in Q5, per the new and old models, respectively. Panel C and D compare the cumulative daily returns to targets in Q1 and Q5, per the new and old models, respectively. For the new model (panel A and C), the number of targets in Q1 (Q5) is 47 (219). The average announcement day return for Q1 and Q5 targets are 14.81% and 11.64%, respectively (significant at the 1% level). The difference in average announcement day return between Q1 and Q5 is 3.17% (not significant at the 10% level). For the old model (panel B and D), the number of targets in Q1 (Q5) is 91(183). The average announcement day return for targets in Q1 and Q5 are 20.32% and 10.63% respectively. The difference in average announcement day return of 9.65% is statistically significant at 5% level.

Two arguments can be forwarded here. First, targets in Q1 outperform targets in Q5, perhaps, because the market partially anticipates that targets in Q5 will receive takeover bids. Second, the targets in Q5 for the new model are less of a market surprise when compared to the targets in Q5 for the old model. Consistent with the arguments, the results in panels A and B show that targets in Q1 generate higher announcement day returns than targets in Q5. The difference in returns to targets in Q1 and Q5 is larger for the old model (panel B) as compared to the new model (panel A), as anticipated. In panel A (B), targets in Q1 generate returns of 14.81% (20.32%) while targets in Q5 generate returns of 11.64% (10.63%) on the announcement day. The difference in announcement returns between Q1 and Q5 (9.69 percentage points for the old model and 3.17 percentage points for new model) is significant at the 5% level for the old model and insignificant for the new model. As discussed above, this difference can be attributed to market surprise as the targets in Q1 and Q5 have the lowest and highest takeover likelihood, respectively.

The results in panels A and C are supported by the results in panels B and D. Panel D (old model) shows that the cumulative returns to targets in Q1 remain below 5.00% until two days before the bid. By the bid announcement day, the cumulative returns are just under 30.00%. Targets in Q5, however, experience a continuous growth in the cumulative returns with more than half of the returns being earned prior to the bid announcement. This suggests that, in the case of the old model, targets in Q1 are less predictable (and more of a market surprise) than targets in Q5. The difference in cumulative returns to targets in Q1 and Q5 is less apparent in the case of the new model, suggesting a limited market surprise element.

Overall, the results suggest the existence of a 'market surprise premium' earned by 'less-predictable' targets (targets in Q1) over 'predictable' targets (targets in Q5) when the bid is announced. As suggested, it can be argued that some of the lower returns earned on the predicted targets portfolio can, perhaps, be attributed to the fact that the market already partially anticipates that targets in predicted target portfolios will receive takeover bids[192]. This market anticipation means that, on average, targets in Q5 are likely to earn lower returns than other targets, and hence the returns to takeover prediction portfolios are likely to be lower than expected. However, the announcement day and cumulative returns earned

[192] An alternative explanation for this observation is that, targets in Q1 are better managed firms and hence command a higher premium than targets in Q5. This argument will also be somewhat inconsistent with the EMH, as it implies that share prices do not already reflect firm performance.

by targets in Q5 of the new model do not differ significantly from those of the old model. The difference in announcement day returns (for example) between both models (1.01%) is not significant at the 10% level. In summary, the results suggest that a lack of a 'market surprise premium' to targets in Q5 partly explain why target prediction models are likely to earn below expected returns. Nonetheless, the results do not explain why the old model outperforms the new model.

7.3.6 The effect of the portfolio management strategy

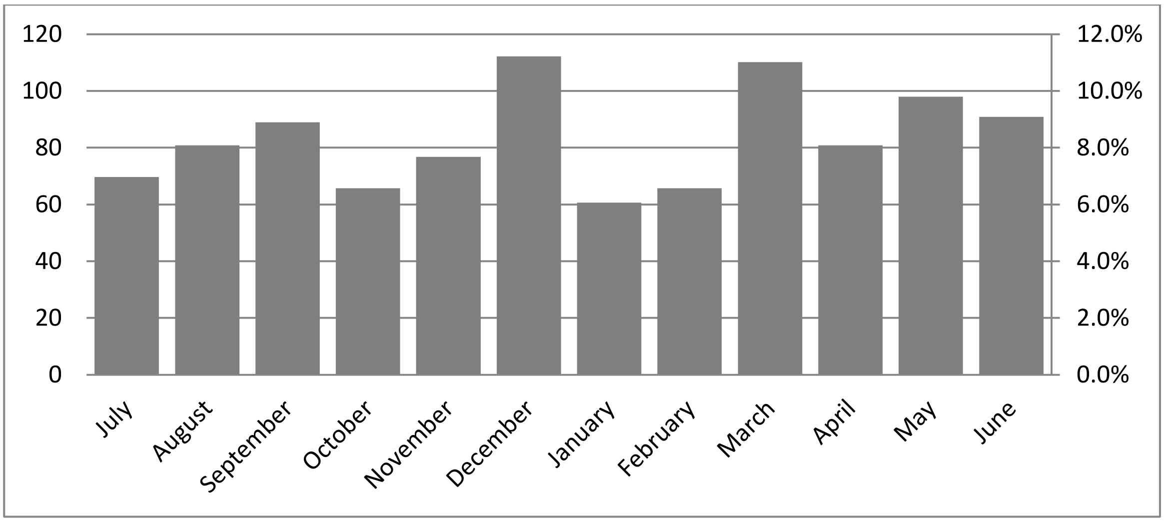
I anticipate that the underperformance of targets prior to takeover bids, as well as, the use of an annual portfolio rebalancing strategy (fixed holding periods from 1st July X1 to 30th June X2) dilutes the returns to takeover target portfolios. The use of a fixed portfolio holding period, while in line with the literature (Soares and Stark (2009)), might mean that targets are invested-in too early, i.e., several months before they receive a takeover bid. Panel A (in figure 7.3.6) shows the distribution of bid announcement months over the portfolio holding period 1st July X1 to 30th June X2 for the targets in the sample. The sample used consists of 990 targets (between 1991 and 2009) out of the 1,323 targets employed in this study[193]. Following the June approach, portfolios are formed on 1st July each year. Nonetheless, only 7.0% of bids are announced in July. A substantial number of bids (50.6%) are announced between January and June – 6 to 12 months after the portfolio formation date.

Panel B shows the market-adjusted returns to takeover targets in the months around the bid announcement date (month -11 to month +11). On average, targets generate negative abnormal returns each month between month –11 and month –3. The cumulative abnormal return earned by targets between month –11 and month –3 is –13.01%. Targets start to generate positive returns in month –2, but the average return earned by targets in month –2 and month –1 is just 3.41%. A substantial portion of the returns to targets is generated in the month in which the bid is announced. I find that targets generate returns of 25.92% in the announcement month and returns of 2.50% in month +1. The cumulative return earned between month –2 and month +2 (–4 and month +1) is 31.55% (30.20%).

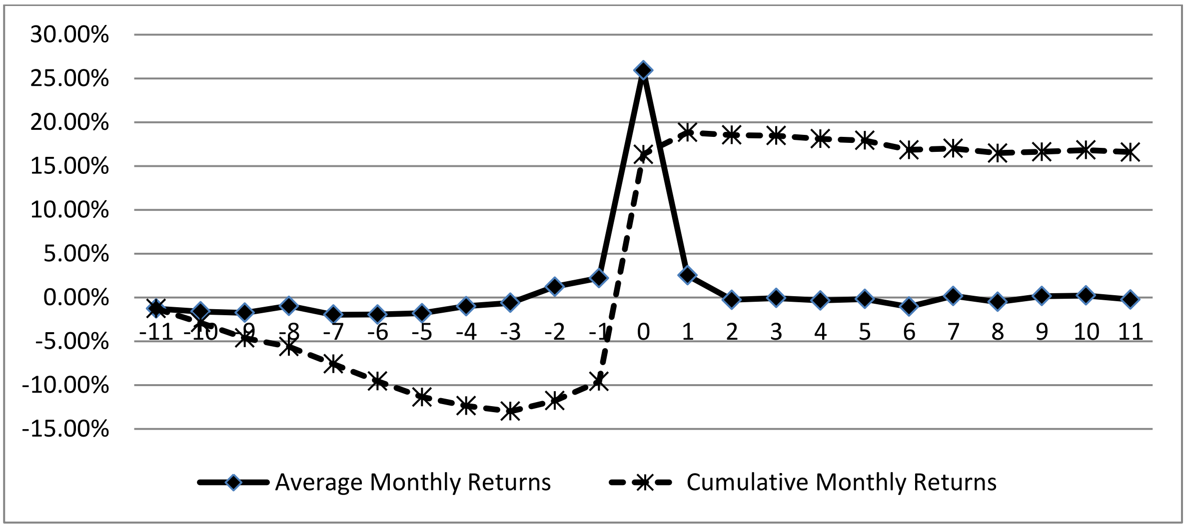
[193] The difference is due to data unavailability.

Figure 7.3.6: Portfolio construction and returns to takeover targets

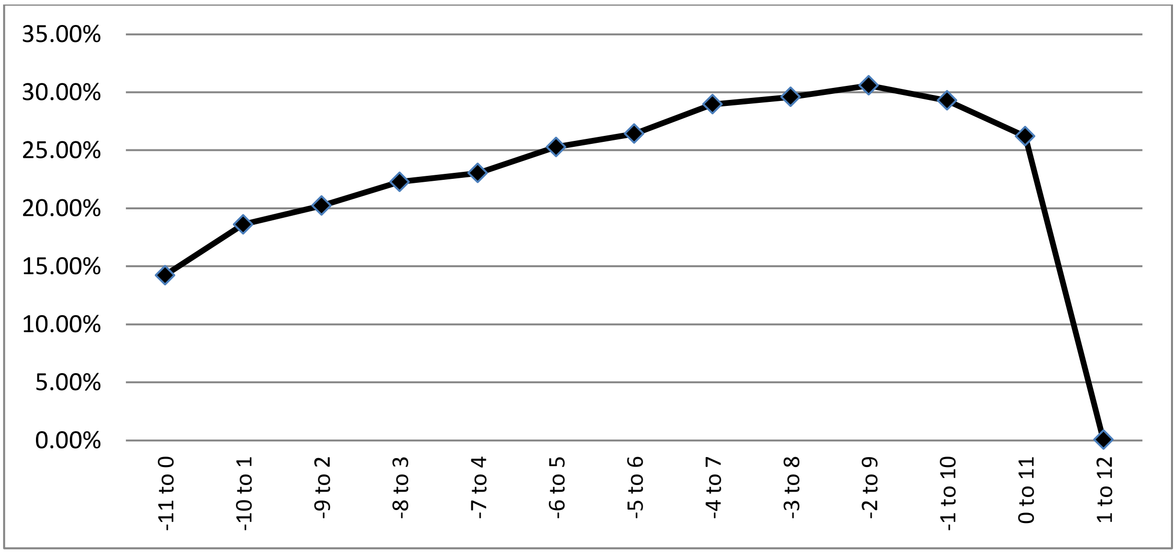
Panel A: The distribution of target bid announcement dates by month



Panel B: Average and cumulative monthly (market-adjusted) returns to takeover targets



Panel C: Cumulative monthly (market-adjusted) returns for different holding periods



Notes: All takeover targets in the sample with available data are used in the analysis. The sample consists of 990 targets (between 1991 and 2009) out of the 1,323 targets employed in this study due to missing data. Portfolios are formed at the end of June each year and held from the 1st July to the 30th June in the next year. Panel A shows the distribution of bid announcement months from July to June. The results show that bid announcements are fairly evenly spread out through the year. While targets are invested-in from July each year, the chart shows that many targets only receive bids several months after the portfolio formation date (1st July). Over 50.6% of targets receive their bids after in the second half of the holding period (January to June). Panel B presents average and cumulative monthly returns earned during the period starting eleven months prior to the bid (month -11) to eleven months after the bid (month +11). Month 0 is the bid announcement month. The analysis employs event study methods to compute the market-adjusted monthly returns to targets around the announcement period. The purpose of this analysis is to show that, on average, targets earn negative returns in the months prior to the bid announcement. The results show that, on average, targets only start to generate positive returns two months before the bid. Panel C shows the cumulative monthly returns generated by targets for different holding periods. The returns of 14.24% to holding period -11 to 0, for example, denotes the market-adjusted returns earned by holding all 990 targets for the twelve-month period starting eleven months before the bid is announced (month -11 to month 0). Likewise, the returns of 0.05% to holding period month +1 to +12, denotes the returns earned by holding targets for 12 months starting the month after the bid is announced.

Overall, this finding highlights the importance of correctly identifying the announcement month and the risk involved with predicting targets too early when predicting targets for investment purposes. The results are consistent with prior studies showing that targets generate significant gains upon merger announcements. These announcement returns are similar (in magnitude) to those reported in some prior studies. For example, Frank and Harris (1989) report announcement month abnormal returns of between 20.6% and 29.1% to UK targets.

Panel C reports the twelve-month cumulative market-adjusted returns to targets for different holding periods around the announcement month. The market-adjusted returns of 14.24% attributed to holding period -11 to 0, for example, is the returns earned by the 990 targets for the twelve-month period starting eleven months before the bid is announced (month -11 to month 0). The results in panel C show that if a holding period from month –11 to month 0 (inclusive) is considered, the average cumulative market-adjusted returns earned by targets is under 14.24%. These returns increase systematically as the start of the holding period is closer to the announcement month. For example, the market-adjusted return for holding period –8 to +3 is 22.27% and the return for holding period –5 to +6 is 26.42%. As expected, the cumulative market-adjusted returns earned between month +1 and +12 (i.e., the twelve-month period starting one month after the bid announcement) is close to zero (0.05%). The highest average cumulative market-adjusted return (30.58%) is earned when the holding period is –2 to +9. These results suggests that holding a portfolio of targets too early (i.e., several months before the announcement month) is suboptimal.

In summary, I show that several targets receive takeover bids several months after they are included in the predicted target portfolio (panel A). On average, targets earn substantially negative returns up to two months before their bid announcement (panel B). In terms of overall portfolio returns, this suggests that the high returns earned by targets in the bid announcement month are partly neutralised by their poor performance in the months prior to the bids. This is supported by the finding that over 50.6% of targets only receive bids six to twelve months after their inclusion in predicted target portfolios. This, perhaps, partly explains why target portfolios earn less-than-expected returns.

7.5 Chapter summary and conclusion

In the previous chapter, it is shown that the new variables introduced in this study markedly improved the predictive ability of previous takeover prediction models. It is shown that the new model can even achieve average target concentrations of up to 11.23% in some portfolios (recursive model Port5%). Given this promising performance, the main goal of this chapter is to test whether, contrary to the EMH, investors can use this model to outperform the market. The results from the analysis show that indeed the new model generates substantial abnormal returns in certain periods. For example, the model generates significant alpha in BULL 1 (July 1996 – August 2000). During this period, the model is able to generate alpha of 2.80% (value weighted portfolios) and 3.40% (equal-weighted portfolios) per month. Nonetheless, the results show that the model performs poorly in certain periods which coincide with periods of market downturn or decline. For example in BEAR 2 (November 2007 – June 2011), the model achieves negative alphas of – 4.10% (equal-weighted portfolios) and – 2.70% (value-weighted portfolios).

It appears the performance of the model during periods of decline is so poor that any gains generated in periods of market growth are completely wiped out by the losses experienced during periods of decline. The long run average performance across several different portfolio selection techniques (deciles, quintiles, cut-offs and fixed portfolios) and different factor models (CAPM, Fama and French three factor and Carhart) is positive but statistically not different from zero. Even when the long run returns are positive (significant at 10%), their magnitude is economically small (e.g., 0.60% alpha generated by value-weighted D10) when compared to results presented in the literature on trading strategies. These results indicate that, on average, the model is unlikely to generate significant (economic) long run returns for investors. The old model, which is less accurate in predicting takeover targets, performs better in an investment setting. The old model achieves long run alphas of up to 3.30% in value-weighted portfolios (Port30). This level of alpha is economically attractive and is unlikely to disappear even when transaction costs are controlled for. The implication of this finding is that success in accurately predicting takeover targets does not naturally lead to superior investment performance.

The second part of the chapter explores potential determinants of the returns to target portfolios (including the presence of type II errors, the inclusion of bankrupt firms, the effects of small firms and the effect of potential market-wide bid anticipation) and attempts to explain why the new model underperforms.

First, I explore whether the presence of non-targets in predicted target portfolios (type II errors) explains the poor performance of these portfolios. Studies such as Cahan et al. (2011) have argued that type II errors are generally poorly-performing firms which are better off being acquired. I do not find evidence in support of this contention. I find that the presence of non-targets does not explain the poor performance of the portfolios. The alpha earned by the portfolios (new and old models) remains unchanged (in terms of magnitude) when all non-targets are excluded. This finding is consistent with Cremers et al. (2009) who report that the positive returns to their predicted target portfolios are not driven by the targets within the portfolios. This finding partly explains why the new model underperforms the old model even though it achieves higher target concentrations.

Second, I investigate whether the presence of bankrupt firms within predicted target portfolios explains their poor performance. I find that the exclusion of all bankrupt firms from the predicted target portfolio improves the alpha of the portfolio. The effect is more apparent in the case of the old model than the new model. The alpha of the old model becomes positive and significant (at the 10% level) when bankrupt firms are excluded from the portfolio. The alpha of the new model increases by 0.1 percentage point but remains insignificant at the 10% level. The results suggest that bankrupt firms within target portfolios have a negative influence on the performance these portfolios.

Third, I explore whether the probable poor performance of the small firms within the portfolios explains the long run performance. I find that the exclusion of small firms from the portfolios leads to improvements in the long run results. For example, the new model generates a significant alpha (of 0.4% per month) when firms with market capitalisation of less than £100 million are excluded from the target portfolios. These results suggest that the presence of small firms within predicted target portfolios negatively impacts on their performance.

Fourth, I anticipate that the underperformance of targets prior to takeover bids, as well as, the use of an annual portfolio rebalancing strategy (fixed holding periods from 1st July X1 to 30th June X2) dilutes the returns to takeover target portfolios. I find that several targets receive takeover bids several months after they are included in the predicted target portfolio. Over 50.6% receive bids six to twelve months after their inclusion in predicted target portfolios. On average, targets earn substantially negative returns up to two months before their bid announcement. This suggests that the high returns earned by targets in the bid announcement month are partly neutralised by their poor performance in the months prior to the bids. This mismatch between the portfolio holding period and the bid announcement month, perhaps, partly explains why target portfolios earn less-than-expected returns.

Fifth, I anticipate that the takeover bids successfully predicted by the new model are also widely anticipated by the market. If this is the case, the share prices of these targets are likely to already reflect the probability that these firms will be subject to future takeover bids. This will mean lower bid announcement returns when such bids are eventually announced. I find evidence in support of this contention. Successfully predicted targets earn lower announcement day returns, on average, when compared to type I errors – predicted non-targets which receive takeover bids. This lower announcement returns to predictable targets partly explains why target portfolios are likely to earn lower-than-expected returns but does not explain why the old model outperforms the new model.

Overall, I find that target portfolios generated using the new and old models outperform the market when value-weighted portfolios are employed. The old model outperforms the new model and its alphas are more economically significant across several portfolios. The finding that the returns to target portfolios are not explained by the presence of targets within these portfolios most likely explains this observation. The presence of small firms, bankrupt firms and type II errors, the effect of market-wide anticipation as well as the mismatch between the portfolio holding period and the bid announcement month negatively impacts on the returns to predicted target portfolios.

CHAPTER 8 CONCLUSION

8.1 Introduction

The main objectives of this thesis were to investigate the characteristics of takeover targets, evaluate whether takeover targets can be predicted using publicly available information, assess whether takeover prediction modelling can form the basis of a profitable investment strategy and – if not – explain why investing in predicted targets is likely to be a suboptimal investment strategy. A UK sample was selected as a suitable sample for the study given its size, the level of takeover activity within the market and its unique institutional features (see sections 1.3 and 1.4). Several interesting findings have emerged from the study. This chapter discusses some of the key findings and presents concluding remarks. The chapter is organised as follows. Section 8.2 summarises the key findings and contributions of the study. Section 8.3 discusses the implications of these findings to research. Section 8.4 discusses some of the potential limitations of the thesis and highlights opportunities for future research.

8.2 Summary and discussion of findings and contributions

8.2.1 Overview

This section summarises some of the key findings and contributions of the thesis. These can be summarised into three categories including (1) the profile of takeover targets, (2) takeover prediction modelling methodology, and (3) investing in predicted targets.

8.2.2 The profile of takeover targets

I empirically test a number of hypotheses which attempt to explain the takeover phenomenon from the perspective of targets. Eight of these hypotheses (including management inefficiency, firm undervaluation, growth-resource mismatch, industry disturbance, firm size, firm age, free cash flow and tangible assets hypotheses) have been investigated in different combinations by prior researchers. These eight old hypotheses are retested in this study using an improved methodology. In addition, I introduce and test eleven new takeover prediction hypotheses. To my knowledge, this study is the first to develop and tests any of these eleven new hypotheses in a takeover prediction setting. These hypotheses are proxied by variables that have been used in prior accounting and finance research. Of the eleven new hypotheses, three hypotheses (including firm size, firm age and capital structure) build on the old prediction hypotheses.

A common theme in this literature is the role of the market for corporate control. The management inefficiency hypotheses generally contend that within an active takeover market, poorly performing management teams will be replaced by more efficient shareholder value maximising management teams. In essence, the market for corporate control enforces managerial discipline. Prior research evidence on the issue is inconsistent. Some US studies such as Agrawal and Jaffe (2003) have shown that this hypothesis is not supported by the data, despite the widely held assertion that the takeover market disciplines poorly performing managers (see, for example, Palepu (1986)). In the opening chapter, I argue that a US sample is, perhaps, not the optimal context to investigate the role of the market for corporate control given confounding effects of state-level antitakeover amendments and the ability of some (entrenched) managers to fend off potential bidders. By employing a UK sample, a broader approach (taking into consideration different dimensions of the management inefficiency concept and controlling for several moderating variables) and an improved methodology, it is shown here that although targets are firms generally experiencing a decline in growth, they are not loss-making firms, on average.

Target firms are, perhaps, inefficiently managed in the sense that they lack future growth opportunities as exhibited by a decline in stock returns as well as a decline in sales growth prior to takeovers. Consistent with this argument, I find that targets experience a monthly decline in share returns between month 11 and month 3 prior to the month of the bid. Further, I find that a firm's takeover probability declines when its Taffler Z score falls below the 0 threshold, suggesting that financial distress (and hence poor management performance) does not increase a firm's chances of receiving a bid. I find evidence in support of Powell's (1997) free cash flow hypothesis – takeover probability increases with firm free cash flow – which is also consistent with the argument that the average takeover target is not financially starved. Contrary to the assertions of Palepu (1986), Morck et al. (1989), Powell (2001), Powell and Yawson (2007) and Brar et al. (2009) but consistent with De and Jindra (2012), I conclude that takeover targets are not loss-making (in an accounting sense) or financially constrained firms as suggested by prior researchers. In this context management inefficiency is, perhaps, limited to management's inability to grow future firm cash flows.

The results from the broad tests of the management inefficiency hypothesis suggest the existence of an active but 'cautious' market for corporate control. Bidders appear willing to bid for firms with limited growth opportunities (as proxied by their market returns) only when such firms have potential for profitability (as evidenced by their past performance). A key question that arises at this point is what happens to firms that consistently perform poorly in an accounting sense (i.e., loss-making firms). The findings of this study suggest that the market for corporate control does not particularly discipline such managers, on average. Perhaps, these managers are disciplined by other forms of reorganisation such as bankruptcy, buyouts, demergers and debt restructuring, amongst others.

The firm undervaluation hypothesis suggests that firms that are perceived to be undervalued will have a higher takeover likelihood. Consistent with prior UK studies (such as Powell (1997, 2004) and Powell and Yawson (2007)), I do not find any support for the undervaluation hypothesis when firm undervaluation is proxied by the book to market ratio. The results show that takeover likelihood rather decreases with the book to market ratio.

The tangible assets hypothesis (Ambrose and Megginson (1992)) contends that takeover probability will increase with the proportion of tangible assets in a firm's portfolio. Consistent with this hypothesis (but contrary to Powell (2004)), I find empirical evidence that UK targets have significantly higher levels of tangible assets when compared to non-targets. These results are robust to industry differences thus indicating that bidders generally show preference for firms with a high proportion of property, plant and equipment within their total asset portfolio. As discussed in section 5.2.7, this tendency could be explained by the fact that the presence of tangible assets signals high debt capacity and reduces information asymmetry. These results lend further support to the existence of a rather 'cautious' market for corporate control with a general scepticism for intangible – perhaps, difficult-to-value –assets.

The old firm age hypothesis suggests an inverse relationship between firm age and takeover likelihood. Building on the lifecycle theory, I propose a U-shape relationship between firm age and takeover probability, with young and old firms having the greatest takeover likelihood. The evidence lends support to the contention that younger firms are more susceptible to takeovers but there is no evidence that old firms equally have a high takeover likelihood. These results do not support some of the literature that suggest that obsolescence increases with firm age forcing old firms to solicit or be more susceptible to takeovers (e.g., Davis and Stout (1992), Agarwal and Gort (2002) and Loderer and Waelchli (2010)). Therefore, the question of what happens to firms as they grow old is still very much open for research. While prior literature suggests that takeovers serve as a medium through which these firms are revitalised (and their assets absorbed by newer, more agile forms of organisations), it is probable that these firms are mainly 'recycled' through other forms of reorganisations such as spin-offs and buyouts. It is also, perhaps, rational to posit that firms continuously develop, revitalise themselves (possibly through the acquisition of younger firms and investment in up-to-date technologies) such that their assets cannot be considered 'obsolete', as suggested by prior research.

Consistent with prior studies, the evidence here neither supports the growth-resource mismatch nor the industry disturbance hypotheses. I find no empirical relationship between a firm's takeover likelihood and its growth-resource dummy or industry disturbance dummy. One plausible reason for this is that the proxies proposed by Palepu (1986) poorly capture the underlying concepts. The industry disturbance dummy variable, for example, takes a value of one when a merger is announced in a firm's industry in any given year and a value of zero otherwise. Due to the high-frequency of merger activity, most firms have an industry disturbance dummy of 1 in most years.

The firm size hypothesis (Palepu (1986)) suggests that small firms will have a higher takeover probability. This hypothesis has been used across several prior studies with inconsistent results. This thesis provides evidence to reconcile apparent discrepancies in earlier research on how firm size affects the probability of receiving a bid. For the first time, it is empirically shown here that when the entire population of listed firms is considered (i.e., a panel data set), and no size restrictions are employed in sample selection, takeover probability first increases with firm size then declines when a threshold is reached. That is, the relationship between firm size and takeover probability is curvilinear or inverse U-shaped. On average, targets are neither the smallest nor the largest firms in the population. The results are consistent with an array of theories including economies of scale, managerial hubris, managerial utility maximisation, empire-building, information asymmetry, and transaction costs (further discussed in section 3.3.2).

This finding explains some of the inconsistencies in prior research as prior research has reported a positive relationship (e.g., Hughes (1989), Mitchell and Mulherin (1996) and

Harford (2005)) negative relationship (e.g., Hasbrouck (1985), Palepu (1986), Bartley and Boardman (1990), Walter (1994) and Brar et al. (2009)) and insignificant relationship (e.g., Powell (1997)) between takeover probability and firm size. These studies construct their samples differently, sometimes focusing on firms in certain industries and above a threshold size. Palepu (1986) focuses on firms in the asset-intensive manufacturing and mining industry. Palepu's sample is likely to be predominantly made up of large firms (natural log of total assets). As shown in section 5.3.2, consistent with Palepu's finding, takeover is negatively related to firm size in the segment of large firms. Similarly Brar et al. (2009) restrict their sample to firms with market capitalisation of at least $100 million. This restriction also skews the sample towards large firms and hence, the results. The results here (test of old firm size hypothesis) are consistent with Powell (1997) who finds no clear linear relationship between firm size and takeover likelihood.

Prior research has reported discrepancies in the relationship between a firm's leverage and its probability of being acquired. The existence of a strictly positive or a strictly negative relationship between leverage and takeover probably is, perhaps, inconsistent with one or more theories of capital structure. This is discussed in section 3.3.3. The evidence in this study suggests that the relationship between leverage and takeover probability is best modelled as an inverse U-shaped relationship. That is, takeover probability initially increases with leverage and then declines as leverage increases above a threshold, all else equal. Firms are likely to take on extra debt when they have growth opportunities that require resources greater than those generated from profit retention. This potential for growth but lack of resources is attractive to resource-rich bidders. Firms with high levels of debt are usually bound by restrictive debt covenants which bidders might find unattractive irrespective of the firm's growth potential. This is consistent with empirical evidence asserting that firms increase leverage to make them less attractive as takeover targets (see, for example, Harris and Raviv (1988), Stulz (1988), Garvey and Hanka (1999)). These results are consistent with a possibility that some UK firms take on extra debt to make them unattractive takeover targets.

The employment effects of proposed M&As is a major concern for regulators as well as employees. It is not uncommon for bidders to make pledges on how the proposed acquisition will affect target employees. In fact, the UK Takeover Code requires bidders to disclose their intensions for target employees (see Takeover Code (2011)). Nonetheless, prior empirical research reveals that mergers, on average, result in loss of employment for target employees, in particular (see, for example, Shleifer and Summers (1988), Haynes and Thomson (1999) Conyon et al. (2002), Kubo and Saito (2012) and Lehto and Bockerman (2008)). In this research, I investigate whether bidders are drawn to certain targets due to potential benefits of restructuring either theirs (the bidder's) or the target's payroll. I find evidence that the probability of receiving a bid initially increases with payroll burden then declines after a threshold is attained. That is, take over probability has an inverse U-shaped relationship with payroll burden. This finding is robust to different model specifications.

As suggested by Shleifer and Summers (1988) and Gugler and Yurtoglu (2004), corporate reorganisation through M&A is an effective way of restructuring corporate human resources as a new management team is less likely to uphold existing employee contracts. Their evidence (Shleifer and Summers (1988) and Gugler and Yurtoglu (2004)) suggests that firms can deliberately engage (as a target) in M&A to create shareholder value by shedding their excess human resources. This argument is consistent with empirical findings that a reduction in payroll costs is one of the main ways of generating synergies in mergers (Devos et al. (2009), Haynes and Thomson (1999) and, Shleifer and Summers (1988)).

Nonetheless, it is shown that the relationship between takeover likelihood and payroll burden does not persist in a linear fashion. High payroll burden, potentially, also acts as a deterrent to takeovers. While the redeployment and divestment (layoffs) of human resources can be a way to create synergies, the associated costs (e.g., compensation and reputational effects), perhaps, result in the creation of negative synergies at very high levels (see, for example, Krishnan et al. 2007). Besides increasing the complexity of the restructuring process, very large layoffs are likely to lead to significant or costly compensation schemes. Such layoffs are also likely to be met with stiff resistance from managers and employees with further effects on retained employee motivation and performance. Further, protracted litigations and court battles with damaging effects on corporate reputation cannot be ruled out.

Mergers within highly concentrated industries are generally subject to more regulatory scrutiny. This is particularly the case in the UK banking and utilities industry[194]. I empirically investigate the relationship between a firm's industry concentration (proxied

[194] As discussed in section 4.2, firms within the banking industry are excluded from the sample used in this study given the unique interpretation of the financial statements.

by its Herfindahl index) and its takeover likelihood. The results reveal that, as expected, a firm's industry concentration is negatively related to its takeover likelihood. This can partly be explained by the legal protection (antitrust laws) that concentrated industries enjoy. Further, firms within low concentration industries (hence highly competitive industries) might see mergers as a way of developing a competitive potential by increasing market size or market power.

The literature holds two contrasting views on the role of share repurchases: (1) as signal of undervaluation and available free cash flow and hence a tendency to increase takeover likelihood or (2) as mechanism to defend against takeovers by consolidating the firm's shareholding (see, for example, Harris and Raviv (1988), Persons (1994), Jagannathan et al. (2000), Dittmar (2000), Grullon and Michaely (2002), Grullon and Michaely (2004), Brav et al. (2005) and Billett and Xue (2007)). The empirical evidence in this study lends partial support to the undervaluation and free cash flow signalling perspective of the share repurchase hypothesis. This implies that UK managers are more likely to repurchase shares when they believe that the firm's stock is undervalued or when they need to distribute free cash flows. This acts as a signal to potential bidders thus increasing the incidence of takeover bids. In summary, I find that share repurchase activity does not act as a deterrent to takeovers as it marginally increases a firm's likelihood of receiving a takeover bid. The relationship is, however, not robust when other determinants of takeover likelihood are controlled for.

Additionally, it is shown that two key market variables (market liquidity and stock market performance) have a significant effect on the propensity for firms to engage in M&A over time. The evidence suggests that that the propensity to engage in M&A increases as market liquidity (or capital availability) increases. In line with the hypotheses, I also find that the likelihood of acquisition increases with the emergence of merger rumours, decreases with the level of potential asymmetry in valuation, and decreases with financial distress. Nonetheless the results obtained for the merger rumours and financial distress hypotheses are not statistically significant when other determinants of takeover likelihood are controlled for.

Overall, the thesis builds on the assertion that our knowledge of factors that drive the takeover decision can be substantially improved. I demonstrate this by identifying several new hypotheses for predicting takeover targets which are tested in this study for the first time. The new model (developed from a combination of the new and old hypotheses) is tested for classification and predictive ability using ROC curve and out-of-sample analysis in chapter 6. The results in chapter 6 show that a model with the new hypotheses (new model) outperforms a benchmark model without the new hypotheses (old model). Also, the results show that, while some of the new variables are found to be statistically insignificant in the regression model, their inclusion in the model significantly improves its performance.

While the new hypotheses substantially improve the performance of prior prediction models, there is no suggestion that this set of hypotheses is exhaustive. Such an argument will be misleading given the, arguably, low pseudo R squares and area under the ROC curve achieved by the model. While the new model improves upon the old model, it does not provide a comprehensive explanation of the phenomenon. An interesting finding is the fact that curvilinear relationship forms can, sometimes, better capture the relationship between certain variables (e.g., firm size, payroll burden and leverage) and takeover likelihood. This suggests the need to also explore the usefulness of nonlinear models in takeover prediction in future research.

8.2.3 Takeover prediction modelling methodology

Besides the use of a limited set of hypotheses, there are several gaps, inconsistencies and biases in the methodologies employed in prior studies – some of which this research addresses. Some of these biases are discussed in section 2.6 and explored in chapters 5, 6 and 7. Prior studies (including Palepu (1986), Barnes (1990, 1998, 1999, 2000), Ambrose and Megginson (1992), Walter (1994) and Brar et al. (2009), amongst others) have mainly employed matched-samples (i.e., equal number of targets and non-targets) in the development of the parameters of prediction models. This leads to significant survivorship bias as firms that are delisted, liquidated or go bankrupt are typically excluded from these samples. Perhaps, the main adverse effect of this strategy is that these models (developed from matched-samples) are not trained to distinguish between targets and bankrupt (or liquidated) firms out-of-sample. Moreover, the matched sample methodology masks the rare event problem by increasing the ratio of targets to non-targets in training samples. While such a strategy might be valid for understanding the characteristics of targets (as discussed in Palepu (1986)), it is unlikely to be effective for out-of-sample prediction. The alternative (adopted in this study) is to employ a panel data set in which each firm contributes an observation in every year over the study period. This sampling methodology is standard in other areas of finance and accounting research.

Further, prior studies employ arbitrarily selected test and holdout periods, with several studies employing a very short (usually one-year) holdout period. I empirically show that the use of a limited holdout period (such as one year), leads to substantial bias and non-generalisable results. I show that takeover prediction models (old and new models) tend to perform better in bull periods than in bear periods. This is, perhaps, because takeovers are more likely to be initiated in bull periods than in bear periods. Additionally, the evidence here also suggests that the length (in years) of the estimation sample plays a role in moderating the performance of the model. I find that the models, generally, perform better when a longer estimation sample (more years of data) is used in developing model parameters. This suggests that the use of more (rather than less) years of data in the development of model parameters is an optimal modelling strategy.

Again, some takeover likelihood modelling studies evaluate model performance by computing returns to predicted target portfolios but do not test whether the model predicts actual targets (e.g., Powell (2001), Cremers et al. (2009) and Brar et al. (2009)). The latter is, perhaps, a more adequate test of a prediction model's performance[195]. Studies employing firm takeover likelihood as an independent variable in research (e.g., Cremers et al. (2009), Bhanot et al. (2010) and Cornett et al. (2011)) do not evaluate whether the prediction models developed can predict actual takeover targets. Such a test is vital to ascertain whether the model is effective in ascribing takeover likelihood to firms. The evidence from this thesis suggests that the models used in these studies are suboptimal in ascribing takeover probability. These models can be substantially improved by including relevant explanatory variables or prediction hypotheses. Moreover, studies that evaluate the model's ability to predict actual targets (e.g., Palepu (1986), Barnes (1998, 1999, 2000) and Powell (2004)) evaluate model performance against poor benchmarks (such as a random selection prediction approach). These comparisons are biased as a model with any predictive power is likely to outperform a random selection approach. Perhaps, a better benchmark for comparison is the performance of a suitable control model. For example,

[195] Cremers et al. (2009), for example, find that their predicted target portfolios generate positive abnormal returns but these returns are not explained by the targets in the portfolio. That is, the returns to the portfolios do not change in magnitude when targets are excluded from the portfolio. This finding suggests that model predictive ability does not explain the returns (if any) to target portfolios

the research design in his study employs the old model as a control model for evaluating the contribution of the new variables.

Several prior studies incorporate substantial look-ahead bias in their analysis by not recognising the time lapse between financial year-ends and the publication of financial results. Several prior takeover prediction studies assume that firm financial data is made public on the balance sheet date. Again, studies employing a matched-sample methodology do not incorporate ‘timing’ – the dynamics between data availability and bid announcement – in the development of model parameters. The June approach is used in this study to incorporate these dynamics while substantially reducing any possibility of look-ahead bias in the analyses.

Last, prior studies typically use an arbitrarily-selected method for identifying the optimal target portfolio from the holdout sample (e.g., the use of cut-off probabilities or deciles). In critique of these prior studies, I show that the results achieved by prediction models are a function of the method (or cut-off) for extracting the target portfolio from the holdout sample. For example, I find that the use of portfolio identification techniques that lead to larger portfolios (e.g., Port5%, quintiles and deciles) generate better results on average.

Given the above sources of bias inherent in methodological choices, the true predictive ability of takeover prediction models can, perhaps, be observed only by averaging out the effect of choice. I therefore employ a more robust framework for predicting takeover targets and testing prediction models by taking into consideration the issues raised above. I employ a continuously-updated (recursive) model and evaluate its performance over a period of 15 years from 1995 to 2009, across different external market conditions. I explore different portfolio identification techniques including deciles, quintiles, percentiles, cut-off probabilities (developed ex-ante) and fixed portfolios (of 100 firms, 50 firms, 30 firms and 10 firms). I compare the performance of the new models against control models (described as ‘the old model’) equivalent to the model used in prior studies. The control models are identical to the new models but employ fewer variables – the old prediction hypotheses. The design of the control model allows any difference in performance to be directly attributed to the eleven new hypotheses.

As part of this study I develop a new prediction model, whose parameters (shown in table 6.2.1a) can be used in future UK studies (or practice) to ascribe takeover probabilities to firms. This new model has a superior classification and predictive ability when compared with previous models. The model is able to correctly predict more firms that subsequently receive takeover bids when compared to earlier models. The results on model performance are robust to several model specifications and modelling choices (discussed above). The model's coefficients are also reasonably stable allowing for the same model coefficients (e.g., those developed in this study) to be used recurrently for up to ten years without substantially reducing the model's predictive power. The importance of such a model is the finding that several contemporary studies use takeover probability as an independent variable in empirical research but the models used in these studies are, arguably, naïve. The model and its parameters can, perhaps, be useful to future researchers[196].

8.2.4 Investing in predicted targets

As one potential application of the new model, I evaluate whether the model can be used as an investment tool to consistently generate positive abnormal returns for investors. The motivation for this test is the consensus that targets gain substantially from takeover announcements (see Jensen and Ruback (1983), Frank and Harris (1989), and Georgen and Renneboog (2003)) and the mixed findings on the subject[197]. I find that despite the model's ability to correctly predict a higher number of targets than prior models, this superior predictive ability does not translate into consistent abnormal returns for investors. The portfolios of predicted targets earn significant (positive) Carhart alphas in certain periods (which broadly coincide with bull periods) but also earn negative alphas in other periods (which broadly coincide with bear periods). When the portfolios are rebalanced annually, the long run Carhart alphas earned from the strategy are not statistically different from zero. This finding is consistent with the efficient market hypothesis given that the model relies on publicly available information to ascribe takeover probabilities. It is also consistent with prior studies (such as Palepu (1986), Barnes (1998, 1999, 2000) and Powell (2001, 2004)) but is based on a more robust methodological framework.

Prior studies, generally, attribute the inability to generate positive abnormal returns to market efficiency. Nonetheless, to date, there has been no explanation of how market efficiency unfolds in this case. That is, no study (to my knowledge) has investigated why

[196] Studies utilising default or bankruptcy risk readily adopt established models such as Taffler Z score and Altman's Z score (together with model coefficients), but no such models are currently available for takeover risk modelling. Although stale model parameters are useful in ascribing takeover likelihood, fresh parameters are shown to yield more optimal results (see section 6.7.4).

[197] Palepu (1986), Barnes (1998, 1999, 2000) and Powell (2001, 2004) find that abnormal returns cannot be earned from the strategy while Walter (1994), Brar et al. (2009) and Cremers et al. (2009) suggest that abnormal returns can be earned by investing in a portfolio of predicted targets.

predicted target portfolios do not generate excess returns on average, despite the substantial returns to targets. Several prior studies (such as Palepu (1986), Barnes (1998, 1999, 2000) and Powell (1997, 2001, 2004)) achieve very low model predictive abilities. Hence, the finding that such portfolios do not generate excess return is generally attributed to the failure to predict a sufficient number of actual targets.

In chapter 7, I extend the literature by empirically investigating why predicted target portfolios are likely to earn lower-than-expected returns for investors. I investigate whether the mediocre performance of predicted target portfolios can partly be explained by (1) the presence of small poorly performing firms in the portfolios, (2) the tendency for predicted target portfolios to hold a high number of bankrupt firms which earn –100% returns upon bankruptcy declaration, (3) the poor performance of the large number of non-targets within the predicted target portfolios and its diluting effect on portfolio returns, (4) market anticipation of impending bids and its erosion of announcement period gains, and (5) the portfolio management strategy.

Prior studies using a matched-sampling methodology (e.g., when matching by size) tend to bias their samples towards larger and more established firms (see Palepu (1986), Powell (1997, 2001), Brar et al. (2009))[198]. These studies (e.g., Palepu (1986)), however, test their models on a holdout sample of all firms in the population. The results from chapter 7 suggest that the presence of small firms in the predicted target portfolio adversely impacts on the portfolio returns. The (positive) abnormal returns to equal weighted becomes statistically significant when small firms (with market capitalisation below £100 million) are excluded from the portfolios.

Consistent with Powell and Yawson (2007), I find that predicted target portfolios tend to hold a high number of bankrupt firms. Presumably, these stocks earn –100% returns upon failure, hence, eroding any positive returns to actual targets within the portfolio. Excluding bankrupt firms from the predicted target portfolios leads to an improvement in the abnormal returns earned by these portfolios. Nonetheless, this cannot be easily achieved in practice. To my knowledge, no prior study in takeover prediction modelling has considered the effects of bankrupt firms (i.e., the –100% returns to the stock) when computing the returns to predicted target portfolios.

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198 For example, Brar et al. (2009) exclude all firms with market capitalisation below $100million.

Prior studies (e.g., Powell (2001) and Cahan et al. (2011)) suggest that the poor performance of predicted target portfolios is due to the underperformance of type II errors (or non-targets) within target portfolios. Cahan et al. (2011) assert that these type II errors, possibly, underperform other non-targets in the population[199]. The evidence in this study shows that type II errors earn positive abnormal returns, on average. Contrary to Cahan et al. (2011), type II errors perform better than non-targets in the lowest takeover probability quintile (Q1). The returns to predicted target portfolios increase when non-targets are excluded. The long run returns to target-only portfolios are positive but not statistically significant.

Further, prior literature has not considered the potential impact of market wide anticipation of impending bids on the announcement period returns to takeover targets. I find evidence that the market anticipates impending bids and incorporates the bid probability into the share prices of future targets prior to the bid announcement period. The effect is that these highly anticipated targets earn lower-than-expected returns in the announcement period. This is attributable to a ‘limited market surprise’ when the takeover bids are eventually announced. This can, potentially, partly explain the lower-than-expected overall return to predicted target portfolios.

The analysis also reveals that the use of a fixed portfolio holding period (July X1 to June X2) together with the annual portfolio rebalancing technique further erodes the gains to predicted target portfolios. I confirm prior empirical evidence that targets earn negative returns up to three months prior to the bid announcement. Hence, the returns to fixed holding period portfolios are, on average, higher when the bid announcement date is closer to July X1 than to June X2. This is because the target underperformance prior to the bid announcement is captured in the portfolio if the bid announcement date is closer to the end of the holding period (June X2). One way of mitigating some of this negative fixed portfolio holding period effect is by employing a monthly portfolio rebalancing strategy. Such a strategy entails active portfolio management which may involve high transaction costs.

[199] The argument advance in the study is that these type II errors (non-targets with a high takeover likelihood) are better-off acquired. Hence, these firms perform poorly if no takeover bids are received.

In summary, this study demonstrates that target prediction models can be improved through the introduction of relevant prediction hypotheses and improved empirical methods for prediction. The thesis highlights weaknesses in the methodologies used in prior studies and empirically shows how some of the choices of prior researchers lead to bias and non-generalisable results. I develop and adopt a more robust modelling and testing framework which allows for the development of a model which can better predict future takeover targets. This model is, perhaps, useful for key stakeholders such as regulators and management who may want to more fully understand the motivations underlying target selection or the likelihood that some firms will be subject to takeover bids in the future. Nonetheless, I find that if all known sources of bias are eliminated, there is no evidence that even an improved target prediction model can help investors to consistently 'beat the market' in the long run. Indeed, an improved prediction model appears to underperform a simple (old) prediction model. Overall, this thesis contributes to the literature in four main dimensions: (1) by extending the literature on the characteristics of takeover targets, (2) by introducing a more robust prediction modelling and testing framework, (3) by providing a simple model which can be used to ascribe takeover probabilities to UK targets in future research and practice, and (4) by providing some suggestions – beyond the generic market efficiency argument – of why takeover prediction as an investment strategy is unlikely to generate high abnormal returns for investors.

8.3 Implications for future research

As part of this research, the impact of methodological choices (such as the length of the estimation period, the methodology for identifying predicted target portfolios and the size of target portfolios) on research results is evaluated. There are generally no strong theoretical arguments for selecting one method over another. I find that these choices – which are arbitrarily adopted by researchers – tend to substantially impact on the reported performance of prediction models. Based on these results, I posit that a more robust and unbiased approach to testing needs to recognise this influences and control for them by evaluating performance across the different modelling choices. This finding extends beyond the takeover prediction literature with implications for research in corporate event (such as bankruptcy) forecasting.

In addition, the results suggest that the use of a short holdout sample period (such as a year) leads to biased and non-generalisable conclusions about the out-of-sample performance of predictive models (see, for example, Palepu (1986), Walter (1994) and Powell (2001, 2004)). This is supported by the evidence that predictive models are more likely to perform better in bull periods than in bear periods. This suggests that true model performance can, perhaps, be ascertained by testing for predictive ability across different market cycles and holdout periods. The emphasis should be on whether the model's performance is consistent over a long out-of-sample test period.

The 'rare event' problem (discussed in sections 2.5.3 and 2.6.2) has motivated the adoption of a matched-sampling approach (as opposed to a pooled-sampling approach) by prior researchers (e.g., Palepu (1986), Ambrose and Megginson (1992), Walter (1994), Barnes (1998, 1999, 2000) and Powell (1997, 2001)). The findings in this study suggest that contrary to previous suggestions, the use of a pooled-sampling approach is, perhaps, a more optimal modelling strategy. This is especially the case when the goal is to allow for model out-of-sample predictive power. This sampling approach allows for model parameters to be trained to identify potential target from a sample of firms.

The evidence in this study also suggests that reliance on the old hypotheses for the development of prediction models by prior studies results in sub optimal models. The use of the new variables substantially improves the model's explanatory and predictive ability. The new takeover target prediction model provides an improved method for ascribing takeover probabilities. I find that stale model parameters (such as those shown in table 5.4.1) can be useful for future researchers if the goal is simply to model takeover likelihood. Nonetheless, fresh parameters are likely to yield more optimal results.

8.4 Limitations of the study

To a large extent, the methods used in the study and the results reported are robust to the choice of techniques applied. Nonetheless, there are a number of areas in which improvements can be made or the current findings extended. These are discussed below.

The data for share repurchases and merger rumours is obtained from Thomson OneBanker. Upon analyses of this data, I find that the data is patchy and can be considered incomplete.

I anticipate that a database such as the Financial Times (used in Holland and Hodgkinson (1994) and Siganos and Papa (2012)) can provide a more comprehensive method for gathering information on merger rumours. This database will require manual data matching which was not an option in the current study given resource limitations. Some studies (such as Siganos (2013) have also shown that Google search volume can even provide a good indication of market anticipation and the existence of rumours of impending takeover bids. Nonetheless, this data is not available for the full period of my study. Future studies can therefore assess the extent to which this new data can improve our ability to accurately predict future takeover targets.

As in several studies in accounting and finance, there is a possibility that the proxies used in operationalising some of the hypotheses do not fully capture the underlying concepts. I employ proxies which reflect the choices of prior researchers but do not fully investigate whether alternative proxies can better operationalise the underlying concepts. For example, I use GRDummy and IDummy as employed by prior studies (including Palepu (1986)) to proxy for growth-resource mismatch and industry disturbance, respectively. I do not find empirical support for either hypotheses but cannot confidently conclude that the hypotheses are not valid. Another example is the measurement of industry concentration using the Herfindahl index. While the index justifiably measures the concept of industry concentration, its construction in this study ignores the significant role played by private (non-listed) companies in industries. Due to data unavailability and insufficiency, only data for public companies is used to compute the index. Clearly, this might introduce bias into the analysis. Future studies should, perhaps, consider private companies in the construction of the index.

Further, in line with prior studies, the book to market ratio is used as a proxy for undervaluation. Improved measures of undervaluation such the decomposed MTB ratio (Rhodes-Kropf et al. (2005)) and price to value measure (Dong et al. (2006)) have been advanced in the literature. Again, residual volatility has been used as a proxy for information asymmetry in this study. It is worth noting that other measures of information asymmetry (such as analyst forecast errors) have also been used in the literature (see Krishnaswami and Subramaniam (1999)). While modelling bankruptcy risk using the Taffler Z score model is in line with prior research (see, for example, Agarwal and Taffler (2007)), there is a real possibility that the model inadequately operationalises the concept. In fact, several studies (including Shumway (2001) and Christidis and Gregory (2010)) have suggested several potential improvements to this model. Future research can, therefore, consider extending the results of this study by exploring other more efficient bankruptcy prediction models.

Consistent with prior studies (e.g., Cremers et al. (2009)), an annual rebalancing methodology has been applied in this study. In essence, portfolios are formed at the start of July each year and held to the end of June in the next year. The results from section 7.3.6, indicates that the use of this fixed holding period erodes some of the potential gains to the portfolios. Future research can consider the use of a more dynamic approach to portfolio rebalancing such as a monthly rebalancing methodology. This strategy might be more complex to execute and more expensive (in terms of transaction costs) but might generate better returns for investors.

The industry classification system used in this study is arguably broad and, perhaps, poorly captures the competitive structure of some industries. For example, firms engaged in manufacturing are grouped under the manufacturing industry even though these firms can be manufacturing unrelated products. This classification system is, however, narrower than that employed in some prior UK studies such as Renneboog and Trojanowski (2007). It also extends prior studies in the takeover prediction literature (e.g., Palepu (1986), Ambrose and Megginson (1992), Powell (1997, 2001, 2004), Brar et al. (2009) and Cremers et al. (200)) which do not control for industry variations.

Finally, the analysis of portfolio returns in this study (as well as prior studies) ignores the transaction costs involved in investing in portfolios of predicted targets. Given that an annual rebalancing strategy is employed, the inclusion of transaction costs is unlikely to significantly alter the conclusions. Given that the old model generated small positive returns, future studies might consider investigating how these returns are affected when transaction costs are considered

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