Three applications of machine learning methods in corporate finance

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Abstract

This thesis focuses on three applications of machine learning methods in corporate finance. The first two applications (Chapter 2 and 3) are dedicated to two applications of double (or debiased) machine learning (DML) on corporate cash holdings, and merger returns, respectively. The third application (Chapter 4) is related to empirical evaluation of the heterogeneous impacts of cost of carry on cash holdings using the causal forest (CF) method. I also provide a comprehensive introduction to machine learning techniques and the potential benefits that these methods can bring to enhance the effectiveness of data analysis in the field of finance (Chapter 1).

The motivation for using DML is the existence of a large number of explanatory variables in the relevant literature. The increase of features in a system probably causes a high degree of non-linearities and hidden complex inter-relationships between covariates. Traditional machine learning methods which rely on the linearity assumption, like LASSO, cannot handle these ill-conditions. Another weakness that such traditional methods suffer from is omitted variable bias. This means that variables that are probably relevant in predicting the dependent variable are left out due to model selection mistakes. The DML method allows the modelling of non-linearities by incorporating specialized machine learning methods like gradient boosting method. In addition, it resolves the omitted variable bias of naïve estimator through double usage of machine learning methods in the step of nuisance functions estimation.

The motivation for using CF is that we aim to examine the possible heterogeneity at the firm-level, instead of estimating the average relationship across all firms. In fact, CF is a random forest based method to examine the possible heterogeneity at the level of individuals. Although such heterogeneity can be detected by conventional approaches such as subsample analysis, such an approach has two shortages: data snooping bias and preventing the development of new theories given sample partitioning based on previous knowledge. CF is a technique to address these challenges. In addition, as a nonparametric method, it does not require the linearity assumption unlike conventional methods.

Chapter 2 compares the relative importance of potential drivers of cash increase among US industrial firms utilizing DML method. The results show that tangible assets and R&D spending have statistically significant and economically important effects on cash holdings.

Cross-sectional analysis illustrates that debt maturity and cost of carry have lost their importance over the years, while intangible assets have become more important. The ranking of drivers is not specific to healthcare and technology sectors, which have recorded the highest increase in cash. The obtained results are robust to alternative machine learners (gradient boosting method, LASSO, regression trees), cash proxies and estimation methods. These findings have important implications for policymakers regarding the reasons for the slow recovery from the Great Recession.

Chapter 3 investigates the informational value of mergers and acquisitions (M&A) return determinants within a short window around the announcement date using DML technique. The results support the predominant role for variables that are assumed to mitigate information asymmetry (e.g., target's number of analysts, and investment advisors for bidder and target) in M&A deals. It also provides strong evidence regarding the significant effect of high-tech deal indicator, which is closely related to the issue of information asymmetry. The obtained results are robust to different benchmarks (random benchmarks and commonly used ones), alternative machine learners (LASSO, gradient boosting method, and regression trees), and windows of different lengths around the announcement date ($CAR(-1,1)$, $CAR(-4,4)$). Overall, findings affirm the prevalence of irrelevant predictors in M&A literature, underscoring the necessity for developing new theories to identify potential predictors in explaining M&A returns.

Chapter 4 examines the heterogeneity in the effect of cost of carry on cash holdings using the causal forest method. Studying the money demand function at firm level, rather than at the average level, it provides evidence that the density of cost of carry effects with entirely negative values during the 1970s and 1980s have been moving into positive territory since the 1990s. This suggests that the breaching of the Baumol-Tobin model's postulation is more relevant in modern times, with low interest rates. Firm size and net working capital are the most important features responsible for causing the heterogeneity in the cost of carry effect. Particularly, firm size exhibits a hump-shaped effect on the elasticity of cash to cost of carry rather than a simple linear effect, contradiction to existing literature. These results remain robust to alternative cash measures and are not driven by omitted variable bias. These findings suggest that policy makers should track the distributional impacts of opportunity cost of money over time to better evaluate the evolution of monetary policy.

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Author's 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.

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Chapter 1: Introduction

"The world's most valuable resource is no longer oil, but data." This intriguing assertion, articulated by *The Economist* (2017), is dedicated to the subject of 'big data' in the digital age.[1] Incorporating the three V's, i.e., volume, velocity, and variety, big data is transforming the finance industry and holds the potential to profoundly influence future research in finance, as noted by Goldstein et al. (2021). With the explosion of big data problems, many technical challenges emerge including (Goldstein et al., 2021):

1) Dealing with a multitude of variables in the actual economic problem
2) Grappling with highly nonlinear impacts or interaction terms among variables
3) Prioritizing prediction economically rather than statistically

Machine learning (ML), as a hallmark of big data research, stands as a pivotal element, serving as the catalyst for finding solutions to these challenges (Nguyen et al., 2023). The first challenge refers to high-dimensional data. Over the past two decades, advancements in technology have revolutionized data collection practices across various scientific domains. In contemporary times, the norm is to gather an extensive array of feature measurements, rendering the collection of nearly limitless data points a commonplace and transformative aspect of research methodologies. Data sets containing lots of features (predictors), usually larger than the observations, are referred to as *high-dimensional* (Martin and Nagel, 2019). In this context, classical approaches like least squares linear regression prove unsuitable, given the challenges posed by the bias-variance trade-off and the potential risk of overfitting (James et al., 2013). The potential for perfect fitting (overfitting) to the training data in the high-dimensional setting results in a linear model that performs extremely poorly on an independent test set, rendering it impractical and noncontributory as a useful model. Researchers can address the challenges posed by high-dimensional data through the strategic utilization of ML techniques. These methods excel at extracting meaningful features from unstructured data, effectively mitigating the risk of overfitting and enhancing the ability to glean valuable insights from complex datasets (Goldstein et al., 2021; James et al., 2013).

Second, interaction and nonlinearity are designed to shed light on why the impact of a specific variable is contingent upon its interaction with another variable, and why the

[1] The Economist, 'The World's Most Valuable Resource Is No Longer Oil, but Data: The Data Economy Demands a New Approach to Antitrust Rules' (6 May 2017), https://www.economist.com/leaders/2017/05/06/the-worlds-most-valuable-resource-is-no-longer-oil-but-data.

influence of a variable is shaped by its specific value within the system, respectively. By acknowledging the complexity introduced by the interplay between variables and nonlinear relationships, theoretical models can more accurately capture the nuanced dynamics within economic systems (Goldstein et al., 2021). Indeed, the success of ML techniques is frequently attributed to their ability to capture and leverage high-order interaction terms between variables and modelling high degrees of nonlinearity (Mullainathan and Spiess 2017). These capabilities enable ML techniques to discern intricate relationships and dependencies within datasets, contributing significantly to their effectiveness in modeling complex systems and making accurate predictions.

Third, the last challenge centers on the development of new economic theories. While identifying statistically significant predictors for an outcome remains a crucial aspect of establishing statistical models, the paramount focus lies in uncovering predictors that hold economic relevance. Broadly speaking, the primary focus of ML methods revolves around diverse applications, all ultimately geared towards prediction (Wasserbacher and Spindler, 2022). In contrast to traditional approaches, ML methods excel at extracting economically relevant information from unconventional data such as text, images, or videos, serving as a pivotal starting point for nuanced economic analyses (Hoang and Wiegratz, 2023). Integrating ML-driven insights into economic analyses not only broadens the scope of research but also catalyzes innovation, offering economists a more comprehensive and data-driven foundation for decision-making.

Though there is no standardized definition of ML, it can be characterized as a set of techniques that autonomously generate predictions from intricate data. Essentially, machine learning employs a function-fitting approach with the objective of discovering a valuable approximation of the function that governs the predictive association between input and output data (Hastie et al. 2009). Mathematically, utilizing input variables denoted as X and an output variable represented as Y, a learning algorithm is utilized to establish a mapping function denoted as F. Fundamentally, the goal is to approximate the relationship expressed by $Y = F(X)$. The objective of ML is to approximate F with a high degree of accuracy. Consequently, when new input data, X, is introduced, the predicted values of the corresponding Y should closely align with the actual values (Nguyen et al., 2023). The two broad categories of ML are supervised learning (SL) and unsupervised learning (UL). The key distinction between SL and UL lies in the availability of prior knowledge. SL relies on a set of input and output variables that are jointly observed for each data point (Hastie et al. 2009). Classification and regression problems are typical examples addressed by SL.

However, obtaining perfectly labeled datasets is not always practical, rendering supervised learning less viable. This is where UL becomes relevant (Nguyen et al., 2023). UL involves solely a collection of input observations for which the joint distribution is known. However, there is no observed output (response). The goal is to directly infer the properties of these observations (Hastie et al. 2009; Wasserbacher and Spindler, 2022). Common methods in UL include nearest-neighbor mapping, k-means clustering, and singular value decomposition (Nguyen et al., 2023).

ML has become a very hot topic across diver range of scientific areas. Particularly, these methods has received considerable attention in finance. ML's application in the expansive realm of finance has been thoroughly investigated for nearly 40 years, initiated by Hawley et al.'s (1990) study, as noted by Aziz et al. (2022), where they utilized neural networks as an aide to financial decision-making. This scrutiny is partly attributable to the widespread availability of data in the financial sector, the diverse range of implementation areas, and the significant economic ramifications associated with financial decisions (Wasserbacher and Spindler, 2022). For a recent review, see Aziz et al. (2022), Dixon et al. (2020), Hoang and Wiegratz (2023), and Nguyen et al. (2023). The applications of ML methods in the field of finance can be delineated into three principal categories: (1) the formulation of superior and innovative metrics, (2) the mitigation of prediction errors in the context of economic forecasting challenges, and (3) the augmentation of the existing econometric toolset (Hoang and Wiegratz, 2023). Despite the widespread popularity of ML in finance, it appears that the application of ML techniques is in its infancy. Bibliometric analysis conducted by Hoang and Wiegratz (2023) reveals that the utilization of ML in finance research is deemed 'relatively new.' ML-related papers constitute approximately 3%–4% of publications in the top three finance journals, namely, *The Journal of Finance*, *Journal of Financial Economics*, and *The Review of Financial Studies*, in 2021.

Recently, a burgeoning field within ML known as causal ML has garnered increased attention and popularity (e.g., Huber, 2023; Sheng and Chu, 2023). While traditional ML methods are often focused on predicting outcomes, as discussed above, causal ML goes a step further to understand the cause-and-effect relationships between different factors. In other words, causal ML involves using ML techniques to infer causal relationships between variables. In this context, the predictive capabilities of ML algorithms in intricate and high-dimensional settings are harnessed to improve the precision of causal estimations. Conventional methods are unsuitable for conducting causal inference in high-dimensional data settings characterized by a high degree of non-linearities and interactions. For example, propensity score matching (PSM) of Rosenbaum and Rubin (1983) is the common method for making causal inference in finance literature. In matching procedure, the researcher tries to find the most similar firms in characteristics that are associated with the dependent variable (Pinkowitz et al., 2016). Although, matching methods have well-established statistical properties (Imbens and Rubin, 2015, p. 345) and accept direct inputs from users providing researchers to incorporate their insight into analysis (Keele and Small, 2021), but quickly break down as the number of covariates increases (Wager and Athey, 2018). For other drawbacks of PSM, see King and Nielsen (2019).

In this thesis, I leverage two innovative causal ML methods, namely double or debiased machine learning (DML) and causal forest (CF), to explore and address three specific puzzles in the domain of finance, as discussed below. The DML method of Chernozhukov et al. (2017, 2018) combines the predictive power of traditional machine learning methods like least absolute shrinkage and selection operator (LASSO) with the identification concept from econometrics literature for estimating causal effects. Suppose we have one variable of interest, say d, in the model that we want to estimate its causal effect, say α, on dependent variable Y. In addition, there exist lots of features X, known as *confounders*, that are simultaneously correlated with d and Y. The 'naïve' approach to estimate α is utilizing ML methods, like LASSO, to identify the most relevant features for prediction and carry these selected variables forward into the inference model. Additionally, we include in the model the variable of interest d. It then estimates the parameter α for all these features using ordinary least squares (OLS), which allows us to perform inference on the parameter estimates. Simulation results of Chernozhukov et al. (2018) indicate that the naïve estimator grossly fails to discover the true value of the parameter of interest. This is because the naïve estimator is prone to the omitted variable bias. This occurs because ML methods excel at capturing features correlated with the outcome variable, ensuring strong predictive performance. However, they may overlook variables that exhibit weaker correlation with the outcome but are more strongly correlated with d. While the omission of these variables does not compromise predictive accuracy, it introduces bias in estimating α, resulting in invalid post-selection inference (Wasserbacher and Spindler, 2022). Relying on two efficient techniques, i.e., cross-fitting and orthogonalization, DML procedure generates an unbiased and approximately normally distributed estimator for parameter of interest. It is also a root-N consistent estimation method, where N is the sample size, for the parameter of interest (Chernozhukov et al., 2018). Owing to these desirable properties, the application of DML has been widespread across different disciplines from accounting and finance to economics and management (e.g., Ellickson et al., 2023; Hansen and Siggaard, 2023; Wang et al., 2023; Yang et al., 2020).

In many applications, it is crucial to understand the impact of an intervention or policy on individuals (individual treatment effect), rather than have a comprehensive and average picture for entire population. It is essential for assessing the effectiveness of various policies, such as studying the impact of advertising or marketing offers on consumer purchases or evaluating the effectiveness of government programs and public policies (Wager and Athey, 2018). Identifying groups of individuals with heterogeneous responses to a program is valuable for managers or regulators seeking to allocate limited resources more effectively. While traditional methods like parametric subsample analysis can be employed for group identification, there is a risk of spurious findings when iteratively searching for subgroups with high treatment levels. This danger arises when only the results for subgroups exhibiting extreme effects are reported, potentially leading to biased conclusions (Davis and Heller, 2017; Wager and Athey, 2018). A prevalent category of causal ML methodologies has emerged to address this issue. A specific group of these methods are developed based on the decision tree algorithm as a foundational framework (e.g., Bargagli-Stoffi et al., 2020, 2023; Hahn et al., 2020; Wang et al., 2018) including CF of Athey et al. (2019) and Wager and Athey (2018).[2] The CF algorithm employs a recursive data space partitioning strategy, seeking to maximize effect heterogeneity while adhering to the honest condition. In line with this *honesty* principle, distinct subsamples are designated for tree growth and effect estimation (Athey and Imbens, 2016, Wager and Athey, 2018). Due to optimal properties, CF has increasingly attracted the attention of financial researchers (e.g., Audrino et al., 2022; Burke et al., 2023; Hodula et al., 2023).

Chapter 2 focuses on the application of DML to address the so-called 'cash puzzle.' In their seminal paper, Bates et al. (2009) document that the average cash-to-assets ratio for the US industrial firms more than doubled between 1980 to 2006. From that time, several authors tried to explain this phenomenon from different perspectives (e.g., Azar et al., 2016, Foley et al., 2007, Harford et al., 2014, He and Wintoki, 2016). Although describing the surge in cash has been the subject of many studies, a major research question remains unanswered:

[2] The decision tree serves as a nonparametric supervised learning technique employed in both classification and regression tasks. Its objective is to formulate a model capable of predicting the value of a target variable through the acquisition of straightforward decision rules derived from the available data (Sheng and Chu., 2023). Models involving discrete target variables are denoted as classification trees, with prediction error assessed through misclassification cost. Conversely, for decision trees handling continuous target variables, they are termed regression trees, with prediction error quantified as the squared difference between observed and predicted values. The overarching term ‘classification and regression tree’ (CART) analysis encompasses both of these methodologies (Breiman, 2017).

What is the primary cause of this phenomenon? To answer this question, we encounter several empirical challenges. First, given growing studies to describe dramatic rise in corporate cash holdings, we are dealing with a high-dimensional set of controls including driver-specific controls and the commonly used ones in the literature, such as firm size, financial leverage, etc. (e.g., Opler et al., 1999). Second, there is ample evidence that the relationship between cash measures and some of the explanatory variables is nonlinear (e.g., Gao et al., 2021, Guney et al., 2007, Ozkan and Ozkan, 2004). Third, one of the main concerns in estimating the effect of a variable of interest on cash holdings is the endogeneity problem and its associated reverse causality. For example, Harford et al. (2014) warn about the endogeneity problem between debt maturity and cash holdings due to jointly determining of the two components. Because in addition to a firm saving cash to hedge against the refinancing risk associated with a loan that has a short maturity, high cash reserves in the firm persuade lenders to offer a short-term loan to such firms. Using appropriate ML methods, DML can easily address the first and second challenges. Regarding the third challenge, it should be noted that DML is indeed a machine learning-based tool to estimate the causal effect of a target variable under the assumption of conditional exogeneity, which states that the target variable is an exogenous one after conditioning on controls. Even if in practice one is not fully convinced about this assumption, the DML method can be combined with instrumental variables (IV) to derive valid estimation on the structural parameters.

The obtained resullts in Chapter 2 reveal that, first, when I consider driving forces separately or simultaneously, tangible assets and R&D expenditures are identified as the first and second most important drivers of secular increase in cash. In contrast, the smallest casual effects (in absolute value) belong to industrial diversification and relation with customers, in separate and simultaneous analysis respectively. Second, some of the drivers (e.g., cost of carry) which are important in the separate scenario lose their influence in the presence of the other drivers in simultaneous scenario, while others gain importance (e.g., intangible assets). Third, I trace the importance of drivers over five-year windows. Findings show that there is an upward (downward) trend in the effect of R&D and intangibles (cost of carry, tangibles, debt maturity) on cash holdings. Fourth, I compare the effect of drivers in the pre, during, and post-financial crisis 2008. I show that, under credit constrained caused by the global financial crisis 2008, the sensitivity of cash to drivers is significantly affected. Fifth, I examine the relative importance of the drivers between health/tech and other industries. It is well-documented that the cash increase is only related to healthcare and technology industries. The DML results suggest that regardless of what sector firms operate in tangible assets and R&D expenditures are the most influence factors on cash decisions made by firms.

The results are robust to alternative cash proxies (cash-to-assets ratio and natural logarithm of cash-to-net assets ratio), machine learners (LASSO, regression trees, and gradient boosting method (GBM)), and econometrics specifications (DML with and without IVs).

In Chapter 3, I explore an additional application of DML technique in the domain of merger and acquisition (M&A). Particularly, I employ DML to identify factors which exhibit significant impact on M&A announcement period returns. Similar to the second chapter, the primary rationale for employing this methodology is grounded in the abundance of explanatory variables introduced in the literature, along with the potential non-linearities and interactions associated with them. Additionally, as previously mentioned, I aim to circumvent the omitted variable bias inherent in the naïve estimator, where traditional ML methods are applied only once to approximate the nuisance function. Importantly, my decision to apply DML in the context of M&A is inspired by a recent application of the Double Selection (DS) procedure proposed by Belloni et al. (2014) within the asset pricing literature. Feng et al. (2020) utilize the DS procedure to evaluate the contribution of new factors introduced between 2012-2016, relative to a rich set of other factors introduced up to 2011. The DS is a two-step LASSO-based procedure to make inference on a low-dimensional set of target variables in the presence of high-dimensional confounders inherently developed based on the linearity assumption. While in DML, there is no pre-specified assumption on the functional form of the nuisance parameters, and hence, the DML procedure has a larger flexibility to model non-linear relation between dependent and target variables.

Analysing a sample of US acquisitions over 1986-2019 yields compelling evidence pointing to the prevalence of irrelevant predictors in M&A literature. Through the application of the DML procedure, we uncover a sparse set of variables that significantly contribute to predicting M&A returns. Particularly, our analysis reveals a predominant role for information-related variables in predicting short-run announcement returns. Specifically, we observe that variables with significant effects on cumulative abnormal returns (CAR) around the announcement dateinclude the target's number of analysts, target advisors, bidder advisors, high-tech deal indicator, and transaction value. In order to bolster the robustness of our findings, I conduct further analyses by assessing the impact of each factor against randomly selected benchmarks (without replacement). Additionally, I extend the exploration by incorporating alternative ML techniques, namely LASSO and regression trees, within the framework of DML analysis. Notably, the results obtained through these supplementary analyses qualitatively reinforce the main findings, contributing to the overall credibility and reliability of this study.

Chapter 4 is devoted to study the sensitivity of corporate money demand to opportunity costs. In line with the Baumol-Tobin model (Baumol, 1952; Tobin, 1956), the opportunity cost, primarily assessed through short-term interest rates, has a negative impact on macro-level money demand. But recent empirical studies suggest that there is not necessarily a negative correlation between these two variables (e.g., Benati et al., 2021). Firm-level evidence also presents mixed empirical results on the cash-interest relation. Azar et al. (2016) confirm that corporate liquidity management is negatively related to the cost of carrying cash. In contrast, Gao et al. (2021) document a non-monotonic relationship between cash holdings and interest rates. Specifically, they show that there is a positive relation between these two concepts in times of low interest rates. In the fourth chapter, I try to explain these seemingly contradictory results on the relationship between corporate money demand and the opportunity cost of holding cash. Particularly, I examine the potential heterogeneity on the effect of cost of carry, introduced by Azar et al. (2016), on cash holdings. To accomplish this, I employ the CF approach developed by Athey et al. (2019) and Wager and Athey (2018). I hypothesize that due to significant variations in firms' characteristics and the composition of liquid assets (e.g., Cardella et al., 2021), a uniform aggregate monetary policy might influence firms' cash holdings differently in terms of both direction and magnitude. Consequently, it is anticipated that certain subsets of firms will handle their liquidity in a manner deviating from theoretical predictions. The firm-level estimation results obtained from the CF method allow us to identify potential heterogeneity in the impact of opportunity costs on money demand. In essence, our approach differs from previous studies by scrutinizing the granular effects of interest rates on money demand, rather than providing an average effect across the entire population.

Examining a large panel of non-utility and non-financial US firms over the past five decades (1971-2019), I find a notable heterogeneous effect of cost of carry on cash holdings. Moreover, cross-section analysis reveals that heterogeneity has become more pronounced over the decades. Specifically, the first instances of non-negative effects were observed during the 1990s. Subsequently, the prevalence of non-negative effects gradually increased, with the likelihood of observing such effects in the 2010s being much higher than in the 1990s: 10% versus 0.3%. Intriguingly, these two findings—increasing heterogeneity and the emergence of positive effects—coincide with two significant changes in the banking sector: the removal of Regulation Q in the early 1980s and the introduction of sweep account programs in the early 1990s. Upon analyzing the importance scores of firm characteristics, which signify their contribution to the growth of the causal tree, I discern that firm size and net working capital stand out as the two most crucial determinants influencing the heterogeneous effect of the cost of carry. Notably, the pattern detected in the effect of size on the cash-cost of carry relation, as revealed by the Generalized Additive Model (GAM), underscores the non-linear impact of firm size on this relationship. This finding contrasts with the results reported by Eskandari and Zamanian (2022). Lastly, an exploration of heterogeneity by industry reveals that the retail trade sector emerges as the most homogenous group in managing cash in response to changes in opportunity costs. The results of this chapter are robust to alternative measures of cash holdings and are not driven by omitted variables bias.

The thesis unfolds through three principal chapters, each dedicated to a distinct application of causal ML techniques within the realm of corporate finance. In Chapter 2, I delve into the application of DML in the analysis of corporate cash holdings. Chapter 3 shifts the focus to another application of DML, this time exploring its utility in the context of M&A. Finally, in Chapter 4, I demonstrate the advantages of employing CF to elucidate contradictory findings surrounding the cash-interest relation.

Chapter 2: Corporate cash policy and double machine learning[3]

2.1 Introduction

Corporate cash reserves account for a significant part of corporate assets in balance sheets and are indispensable for corporate operations. Firms hoard cash for a variety of reasons including avoiding transaction costs associated with converting noncash assets into cash for payments to customers and suppliers (Azar et al., 2016), and avoiding expensive external financing due to information asymmetry between insiders and outsiders (Ozkan and Ozkan, 2004, Kim et al., 1998). In addition, according to the precautionary motive, firms may raise their cash stockpile to take advantage of future investment opportunities (Opler et al., 1999). Other strategic motivations to save cash are financing innovations and challenging rivals' bottom lines through aggressive pricing in uncertain competitive markets (Lyandres and Palazzo, 2016, Fresard, 2010).

Various theories have been proposed in the literature to elucidate the rationale behind corporate cash decisions, many of which stem from the field of capital structure. Among these, two prominent theories are the pecking order theory and the trade-off theory. The pecking order theory, formulated by Myers and Majluf (1984), posits that firms exhibit a hierarchy of preferences when financing their liquidity requirements, akin to the prioritization observed in capital structure determinations. According to this theory, there is no specific optimal level of cash (e.g., Opler et al., 1999). Instead, firms commence by utilizing internal resources such as retained earnings to address their cash needs. If internal funds prove inadequate, they may resort to external financing options, including the issuance of debt and equity. An alternative view to the pecking order theory of cash holdings is that firms identify their optimal level of cash by balancing the benefits and costs of holding cash (trade-off model of cash). The costs include the opportunity cost of not investing the cash, while the benefits include the flexibility and risk reduction associated with having liquidity.

[3] This Chapter has been presented at several conferences including 2022 Annual Conference of the Money, Macro and Finance, University of Kent, the 2023 Financial Management Association (FMA) European Conference, Aalborg University, the 2023 Finance and Business Analytics (FBA) Conference, Lefkada, and the 2023 Economics of Financial Technology Conference, University of Edinburgh.

The last two decades have seen phenomenal growth in the theoretical and empirical literature seeking to explain why firms hold cash. Much of the previous work uses accounting ratios and other publicly available information in reduced-form models in order to determine firms' propensity to accumulate cash. More recent studies propose new factors (or drivers), thus creating a high-dimensional set of potential determinants of cash holdings. However, the literature has not settled on a universally accepted set of the most salient determinants of cash holdings. Using ML techniques across an extensive sample period, the present study aims to exploit complex patterns and high dimensionality in cash behavior and quantify the relative importance of its determinants. In addition, we examine the evolution of the factors that cause changes to firms' cash holdings over time and across industries.

Machine learning tools gain prominence in corporate finance applications amid advances in computer technology (see, for example, Gu et al., 2020; Amini et al., 2021). In this study, we rely on the cutting-edge double (or debiased) machine learning (DML) procedure of Chernozhukov et al. (2017, 2018), which connects the theoretical work on nonparametric and semiparametric methods with machine learning. It is a framework for casual inference that provides estimates that are 'root-n-consistent'. DML is particularly appealing in the context of cash holdings for the following reasons. First, changes in cash holdings are infrequent, vary over the business cycle, involve discontinuous adjustments, and in the presence of investment lumpiness and costly external finance, there is a nonlinear cash policy (Almeida et al., 2004; Tsoukalas et al., 2017). Therefore, machine learning models that fit complex, nonlinear functional forms can lead to substantial improvement in prediction accuracy.

Second, identifying the most relevant predictors from an extensive set of candidate variables, without considering a preselection, can prove challenging leading to omitted variable concerns, a decrease in modelling accuracy and less reliable estimates (see Falato et al., 2020; Gao et al., 2021). The DML uses machine learning methods twice during the nuisance functions estimation steps and any relevant cofounders not selected in the first step (due to potential selection mistakes), will be selected in the second step. Hence, DML can handle the omitted variables bias (see Belloni et al., 2014; Feng et al., 2020).

Third, nonlinearities and interactions are rooted in the relation between cash holdings and its determinants.[4] The DML algorithm searches for such patterns and does not require any prespecified assumptions about the functional form of the nuisance parameters. In addition, it does not suffer from the regularization bias of nonparametric regressions. Hence, it has

[4] Appendix 2.6 gives a glimpse at the nonlinealities in our sample.

greater flexibility to model the potential nonlinear relationship between cash holdings and firm-level explicators and evaluate the importance of the latter in driving the relationship.

We exploit a sample of US firms, sourced from various databases including Compustat North America, the Federal Reserve Economic Data (FRED) and OECD Tax Database over 1980 to 2019. Our empirical analysis covers two stages. First, we estimate a baseline regression in the spirit of Opler et al. (1999) and Bates et al. (2009) to investigate the main drivers of cash accumulation. In the second stage, using the DML method, we estimate the causal effect of a set of new drivers, which we call 'under-investigated', on corporate cash holdings. We do so by considering a large number (high-dimensional) of potential factors on their own and by pooling them together. We recognize that the importance of the drivers evolves over the years, and some variables may become more or less important in explaining firms' cash holdings. Put differently, both changes in firm characteristics and the sensitivity of firm cash holdings to firm characteristics may explain the cash hoarding phenomenon over the past years (He and Wintoki, 2016; Begenau and Palazzo, 2021). Hence, we trace the causal effect of the DML-selected firm-level drivers over five-year windows to gauge the evolution of our drivers over a long period of time.

As well as considering the variation of cash holdings over time, we argue that the significance of the firm drivers in explaining cash holdings is likely to differ across industries. The rationale for this argument stems from recent empirical regularities suggesting that cash holdings of US firms have grown significantly over the past years, but this increase is mainly concentrated in the high-tech sector. Specifically, R&D intensive and high-tech firms have tripled their cash-to-asset ratios since 1980 compared to their counterparts (Booth and Zhou, 2013; He and Wintoki, 2016). This observation reflects the large number of young and high-growth firms that populate the high-tech sectors. For these firms, hoarding cash enables them to pursue their investment projects. Given that the high-tech sector has become increasingly important for the US economy, and the differences between the high-tech firms and traditional firms in terms of operations and financial policies (Booth and Zhou, 2013), we propose to examine the role of industry-level heterogeneity in cash holdings.

Previewing the main findings, first, we show that several firm-specific drivers contain information about firms' cash holdings. When we apply the DML technique we reveal that some drivers that have economic significance in the existing literataure, lose their effect in the presence of the other drivers (e.g., cost of carry and relationship with customers), while others gain importance (e.g., intangible assets). In addition, the magnitude of the drivers evolves over the years, suggesting that some factors gain importance while others diminish. This points to changing firm characteristics as a major explanation for why firms hoard cash. Related to this finding, we reveal that the underlying relationship between cash holding and the firm-level drivers is significantly different during crisis times compared to tranquil times. We also show the association between cash holdings and financial ratios is driven by firms opearting in high-tech and healthcare industries. This suggests that the sensitivity of cash to financial variables not only depends on firms' net worth, but also on industry-level characterstics.

Our study makes several contributions to the existing literature. First, we estimate for the first time the causal effect of the nine more popular drivers of cash holdings both individually and simultaneously using a number of control variables that may intreact with each other. Our findings extend and supplement the studies of Fernandes and Gonenc (2016) and Falato et al. (2020) that examine the causal effect of a subset of our drivers with regression frameworks.

Second, we speak to the line of work that examines whether the sensitivity of firm cash holdings to firm characteristics has changed over time (e.g He and Wintoki, 2016 and Begenau and Palazzo, 2021). We show that R&D expenditures, tangible assets, intangible assets, cost of carry and multinationality are stable drivers over our sample. On the other hand, tax costs of repatriating earnings debt maturity, diversification and relationship with customers do not have a stable causal relationship with cash holdings. A finding that highlights the dynamic nature of cash holdings and our drivers and is overlooked by the related literature.

Third, we demonstrate that the causal effect between our drivers and cash holdings differs across high-tech and healthcare industries and the rest of our sample. In this sense, we add to the discussion of He and Wintoki (2016), Booth and Zhou (2013), Graham and Leary (2018) and Li and Luo (2020), who argue that cash holdings of high-tech and healthcare industries behave differently than their counterparts.

Finally, we add to the litertaure that explores ML to assess firms' finacial choices. Specifically, Amini et al. (2021) argue that ML teachniques are likely to be applicable to studies sthat examine firms' real decsions such as investment or cash holdings. Our study is the first, as far as we know, to provide a systematic empirical analysis of DML in cash holdings.[5] This is important because compared to the methods applied in the previous related

[5] Although we can find a few studies in literature which take advantage of traditional ML methods to predict cash holdings. Utilizing two machine learning procedures, i.e., decision trees and random forests, Arora et al.

literature, our approach allows us to make inference on a low-dimensional set of factors in the presence of high-dimensional, nonlinear and complex predictors using a standard machine learning technique. Therefore, we provide a parsimonious set of predictors that can be readily implemented by investors, managers and policy makers.

The rest of the chapter is laid out as follows. In section 2 we discuss the relevant literature. In section 3 we describe our methodology. Section 4 presents the data and summary statistics. In Section 5 we report the empirical results and our robustness tests. Section 6 concludes the chapter.

2.2 Background literature

The ground-breaking empirical work of Kim et al. (1998) and Opler et al. (1999) has been extended by numerous studies to identify the determinants of cash holdings. The implication of this literature, which is reviewed by Graham and Leary (2018) and da Cruz et al. (2019), is that the determinants of cash holdings can be broadly categorized into three groups.

The first group relates to studies that explain the level of cash holdings based on firm-specific variables. Kim et al. (1998) conduct the first such study examining the determinants of cash holdings by US firms from 1974 to 1995. They show that an optimal level of liquidity has a direct relation to the cost of external financing, cash flow volatility and investment opportunities. In the context of European countries, Ferreira and Vilela (2004) show that cash holdings are positively affected by the investment opportunity set and cash flows, and negatively affected by an asset's liquidity, leverage and size. Focusing on private firms in the Italian capital market, Bigelli and Sánchez-Vidal (2012) observe that corporate cash holdings decrease with firm size, effective tax rate and financing deficits. By contrast, cash reserves increase with cash flow volatility and cash conversion cycle. Iskandar-Datta and Jia (2012) examine the evolution of cash holdings and their characteristics in seven industrialized countries, including Australia, Canada, France, Germany, Japan, the UK and the US, across 1991-2008. They report that cash increase is a common feature among these countries, except for Japan. Furthermore, they find that the secular cash pattern is

(2019) identify the important drivers of liquidity decisions made by the Canadian firms. Avramov et al. (2021) deploy the LASSO regression to assess the ability of a new text-based measure of downside risk in predicting corporate policies including cash holdings. Elyasiani and Movaghari (2022) apply a robust version of the LASSO method to identify the most important determinants of corporate cash holdings. In none of these studies, machine learners are used to estimate the causal effects of cash holdings determinants. While we employ different ML techniques (i.e., GBM, LASSO, regression trees) in the framework of DML method to conduct causal effect analysis.

explainable by the time-varying firm-specific variables only in Canada, France, the UK and the US.

Initiated by Dittmar et al. (2003), the second group focuses on corporate governance variables. Dittmar et al. (2003) indicate that the importance of some firm-specific variables (such as investment opportunities) in determining the level of cash holdings decreases in poor shareholder protection environments. Harford et al. (2008) show that firms with weaker corporate governance have smaller cash reserves. This is due to managers' opportunistic behaviour under weak corporate governance, which incentivizes managers to waste cash on acquisitions and capital expenditures, and firms' cash reserves will thus decrease. Chen et al. (2012) report that after the split share structure reform, one of the most important reforms on Chinese firms’ governance systems which commenced in 2005, cash reserves of Chinese firms significantly decreased. They attribute this finding to better incentive alignment between controlling shareholders and minority shareholders under the reform. By analysing a sample from fifty-nine countries, Chen et al. (2018) document a strong positive relation between cash holdings and state ownership.

Finally, a strand of the literature pays attention to macroeconomic variables as cash holdings predictors. Curtis et al. (2017) introduce inflation as the key factor for observed changes in the evolution and dynamics of corporate cash holdings in US firms. In addition, Phan et al. (2019) examine the relation between economic policy uncertainty and firm cash holdings. They show that policy uncertainty, measured by the BBD index of Baker et al. (2016), is positively related to firm cash holdings. Moreover, this relation is more pronounced for firms that rely on government spending. Finally, Zhang et al. (2020) investigate the effect of oil price uncertainty on cash holdings of Chinese firms over 2007-2016. Utilizing the crude oil volatility index (OVX) proposed by the Chicago Board Options Exchange (CBOE), they find an inverted U-shaped relation between oil price uncertainty and cash holdings.

The studies discussed above provide a useful background for the linkage between firm- and macro-specific characaterics and cash holdings. Yet, the above studies do not take into account concerns about omitted variables bias or misspecification, nor do they employ cutting-edge econometric methods to explain the magnitude of the drivers. In this chapter, we ask how important under-investigated measures of firm-level drivers are in determining cash holdings. In the sections that follow we turn to our econometric modeling strategy and data.

2.3 Methodology

Following Belloni et al. (2014) and Chernozhukov et al. (2018), we consider the following partially linear regression (PLR) model to estimate the causal effects of the under-investigated drivers on corporate cash holdings:

$$Y_{it} = \theta_0 D_{it} + g(X_{it}) + U_{it} \tag{2.1}$$

$$D_{it} = m(X_{it}) + V_{it} \tag{2.2}$$

where $i = 1, 2, \ldots, N$ refers to firms for time period t. Y_{it} is the dependent variable measured as cash-to-net assets or cash-to-assets. D_{it} stands for the firm-level drivers (or treatment), X_{it} is a set of twenty-five control variables or cofounders, and θ_0 is the parameter of interest (causal effect) that we wish to estimate.[6,7]

The error terms U_{it} and V_{it} are mean zero conditional on the respective right-hand side variables (i.e., $E(U \mid X, D) = 0$ and $E[V \mid X] = 0$ in Equations (2.1) and (2.2), respectively). The nuisance functions m and g are any arbitrary function of controls (or confounders) X that are correlated with both firm-level drivers (D) and dependent variables (Y). Equation (2.1) is the main equation, while Equation (2.2) characterizes the confounding factors, namely the dependence of the firm-level drivers (D) on the controls (X) (Chernozhukov et al., 2018, Bach et al., 2021). By enabling consideration of complex relations through the nuisance functions (i.e., m and g), the above model makes it possible to characterize the nonlinearities between cash measures and its determinants previously shown in literature. In addition, using machine learning methods twice during the nuisance functions estimation steps in DML helps overcome the omitted variables bias. To elaborate, relevant confounders, which are not selected in the step of estimation g due to potential model selection mistakes, will be selected in the step of estimation m (see Belloni et al., 2014).

In our context, we consider D exogenous after conditioning on controls X, an argument that is well supported by the related literature.[8] In other words, we consider our drivers to be exogenous after conditioning for the firm size, dividends, financial leverage, growth opportunities, cash flow, cash flow volatility, net working capital, acquisitions, net working

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[6] In the case of binary treatments, θ_0 equals to the average treatment effect (ATE) in the potential outcome framework (e.g., Chernozhukov et al., 2018, Yang et al., 2020).

[7] In simultaneous analysis, when we consider all drivers at the same time (i.e., the case where D is a vector of drivers), we repeat Equation (2.2) for each element.

[8] See, for example, Bakke and Gu (2017) for diversification, Byun et al. (2021) for debt maturity, Campello and Gao (2017) and Cardella et al. (2021) for cost of carry, Fernandes and Gonenc (2016) for multinationality, Foley et al. (2007) for tax costs of repatriating earnings, He and Wintoki (2016) for R&D, Lei et al. (2018) for tangible assets and Marwick et al. (2020) for intangible assets. More details on the role of the cofounders in the context of our method is available in the Appendix 2.1.

capital, etc. However, to mitigate further any endogeneity concerns, we estimate our models using instrumental variables (IV) in DML (see, Chernozhukov et al., 2018). If anything, our findings are robust to this modification.

Cross-fitting and Neyman orthogonal scores are the two key elements in the DML procedure (Chernozhukov et al., 2018). To illustrate how the DML method utilizes the cross-fitting technique, we explain the simplest case: the two-fold cross-fitting. Consider two sub-samples (K = 2) and denote the resulting sub-samples as I and I^c. In the first step, two nuisance functions *m* and *g* are estimated by sub-sample I^c (the auxiliary sample) where the first estimation is based on *D* and *X* while the second one requires *Y* and *X*. Then, the DML estimator is computed by applying the estimated functions on sub-sample *I* (the main sample). In the second step, we switch the roles of I and I^c, such that *m* and *g* are obtained from sub-sample *I* and the DML estimator is estimated using the data from sub-sample I^c. The final cross-fitting estimator for θ_0 is the simple average of the two DML estimators obtained from the two steps. Chernozhukov et al. (2018) recommend that "… *moderate values of K, such as 4 or 5, work better than K = 2 in a variety of empirical examples and in simulations*" (p. 24). Both the auxiliary and main samples are selected randomly. Thus, it is unlikely that the DML estimation results are influenced by potential trends in the data space.

Neyman orthogonalization eliminates the bias associated with the naïve estimator.[9] It reduces the modelling and the regularization biases of the ML estimators. Given the many regressors that we use as confounders in the relationship between cash holdings and drivers, nonparametrically estimating the nuisance function *g* with a consistent machine learning method and plugging into the naïve estimator, which is described below, causes the estimator to be heavily biased. Working with the Neyman orthogonal scores, DML reduces the sensitivity of the causal effect estimation with respect to high-dimensional nuisance parameters, in comparison to nonparametric regressions (Chernozhukov et al., 2018; Yang et al., 2020). In fact, eliminating bias due to the regularization of the nuisance function in the semi-parametric model (1) is an appealing feature of DML making it attractive for this study, which is characterized by many cash holdings determinants.

[9] In statistics, the Neyman orthogonality condition is defined as $\partial_\eta E[\psi(Y, D, X;\ \theta_0, \eta)|_{\eta=\eta_0} = 0$, where ψ is called the Neyman orthogonal score function, ∂ is the derivative operator and η denotes nuisance functions (m and g) with population value η_0. This condition is responsible for eliminating the impact of bias in high-dimensional nuisance functions estimation with a candidate ML method on subsequent estimation and inference (Bach et al., 2021).

If one believes that could have a well approximation for g, say $\hat{g}$, using some machine learning methods (e.g., LASSO, random forest), a naïve estimate of θ_0 (least squares estimator), regardless of the second equation, is:

$$\widehat{\theta_0} = \left(\frac{1}{n}\sum_i \sum_t D_{it}^2\right)^{-1} \frac{1}{n}\sum_i \sum_t D_{it}(Y_{it} - \hat{g}(X_{it})) \tag{2.3}$$

where n is the number of firm-year observations. Theoretically and numerically, Chernozhukov et al. (2018) show that the naïve estimator has a slow rate of convergence to the true parameter. They prove that 'partialling out' the effect of confounders (i.e., X) from D to obtain the orthogonalized regressors can obviate the biasedness from the naïve estimator and create an efficient estimation for the parameter of interest. After estimating m and g (say, $\widehat{m}$ and $\hat{g}$) using a machine learning method, the double machine learning estimator of θ_0 is defined as:

$$\widetilde{\theta_0} = \left(\frac{1}{n}\sum_i \sum_t \hat{V}_{it} D_{it}\right)^{-1} \frac{1}{n}\sum_i \sum_t \hat{V}_{it}(Y_i - \hat{g}(X_{it})) \tag{2.4}$$

where $\hat{V} = D - \widehat{m}(X)$ is the obtained residual from Equation (2.2). This DML estimator has a desired convergence rate to the true parameter and is approximately normally distributed (Chernozhukov et al., 2018).

In summary, the DML procedure in our context combines the predictive power of machine learning techniques with cross-fitting and orthogonalization to estimate the causal effect of a firm-level driver. A question may arise as to which machine learning method should be used for nuisance parameters estimation. According to Chernozhukov et al. (2018), estimation results based on any 'sensible' machine learning method should be similar. On the other hand, Yang et al. (2020), via a set of simulations, show that the DML in combination with the gradient boosting of Friedman (2001) produces 'fairly robust' results in comparison with other machine learning techniques (such as the random forest, regression trees and the support vector machine). Thus, we base our main empirical results on the gradient boosting learner, and as a sensitivity analysis, we repeat our main estimations with LASSO and regression trees.[10] To estimate the hyperparameters of the learners (i.e., shrinkage parameter in LASSO, complexity parameter in regression trees, number of trees in gradient boosting), we apply 10-fold cross-validation (CV), following Yang et al. (2020).

[10] We provide a short description of the gradient boosting in Appendix 2.2.

As discussed before, one of the main objectives of this chapter is to study the causal effect of the drivers on corporate cash holdings in a multidimensional setting. Thus, we face the risk that we falsely reject the null hypothesis of no significant causal effect of a driver (else, the risk of having a Type I error or a false discovery). Adjusting *p*-values in a multiple hypothesis testing is necessary to valid simultaneous inference at a given significance level (e.g., Harvey and Liu, 2020). Otherwise, the actual probability of falsely rejecting one or more hypotheses will exceed the prespecified level. In our setting, where we examine nine drivers, if we examine them through single hypothesis tests and at a significance level of 5%, the probability of observing at least one significant result is 37%, even if all drivers are actually insignificant. We control for false discoveries by incorporating the step-down procedure of Romano and Wolf (2005).[11]

2.4 Data and summary statistics

2.4.1 Data sources

Our dataset is drawn from different sources. We collect annual accounting reports from Compustat North America over the period 1980-2019. We augment the dataset with the Historical and Customer Segments from Compustat-Capital IQ to obtain data on firms' sales to customers, foreign sales and the number of business segments. The data for macroeconomic variables are taken from the Federal Reserve Economic Data (FRED) database. We also obtain data for taxes from the OECD Tax Database.

Following Opler et al. (1999), we exclude financial (SIC codes 6000-6999) and utility firms (SIC codes 4900-4999), which are subject to greater regulatory supervision. In addition, following prior studies, we extract firm-year observations with positive book value of assets. We also drop firm-year observations with negative cash, sales and book value of equity, and set missing values of R&D to zero (see Bates et al., 2009 and He and Wintoki, 2016). To mitigate the influence of outliers, we winsorize all the regression variables at the 2nd and 98th percentiles. Our final panel, which is unbalanced, consists of 35,294 firm-year observations from 6,737 unique firms.

2.4.2 Choice of variables

Following Bates et al. (2009) and Opler et al. (1999), our primary measure of cash is the logarithm of the ratio of cash and short-term investment to net assets (i.e., book value of

[11] As a robustness check, we also adjust the *p*-values based on Bonferroni correction and Benjamini and Yekutieli's (2001) procedure.

assets minus cash and short-term investment). Our main explanatory variables, which are under-investigated in the literature, consist of nine determinants of cash holdings employed by previous studies. Specifically, we use R&D spending (He and Wintoki, 2016), intangible assets (Falato et al., 2020), tangible assets (Lei et al., 2018), tax costs of repatriating earnings (Foley et al., 2007), cost of carry (Azar et al., 2016), debt maturity (Harford et al., 2014), diversification (Duchin, 2010), relationship with customers (Itzkowitz, 2013) and multinationality (Fernandes and Gonenc, 2016).

We also rely on firm-level control variables introduced by Opler et al. (1999) to explain firms' cash holdings. The basic controls include market-to-book ratio, financial leverage, a dummy variable to indicate dividend payments, cash flow, cash flow volatility, net working capital, acquisitions, capital expenditures and firm size. In addition, we employ sixteen firm-specific controls, which are intended to measure different aspects of firms' financial health (see Foley et al., 2007; He and Wintoki, 2016; Subramaniam et al., 2011). These include foreign income, domestic income, net debt issuance, net equity issuance, effective tax rate, Altman's Z-Score, negative income, firm equity issuance volatility, industry equity issuance volatility, over-investment, sale of PPE dummy, loss (gain) of selling PPE and investment, profitability, profit volatility, net investment and sales growth.[12]

2.4.3 Summary statistics

Table 2.1 presents descriptive statistics for the cash proxies (Panel A), the basic control variables (Panel B) and the under-investigated drivers (Panel C). The average cash-to-assets ratio is 12.5% during the sample period. This statistic is slightly lower than the corresponding value of Bates et al. (2009). However, the authors rely on a different time period and a different sample of firms due to the limited choice of explanatory variables.[13] We also observe that the mean of cash flow, for example, is 4.1%, and this is very similar to the figure reported by Opler et al. (1999).

Table 2.1 Summary statistics

	No. of observations	Mean	Sd.
Panel A: Dependent variables			
Cash-to-net assets	35,294	0.186	0.276
Cash-to-assets	35,294	0.125	0.138
Panel B: Basic controls			
Firm size	35,294	5.287	2.319
Growth opportunities	35,294	1.610	0.956

[12] See Appendix 2.3 for precise definitions of the variables used in this study.
[13] Consistent with Bates et al. (2009), the time series plot of cash-to-assets ratio in Appendix 2.7 illustrates the secular upward trend in cash holdings in our sample, confirming the suitability of the sample to investigate the causal effects of the drivers behind the trend.

Financial leverage	35,294	0.251	0.170
Dividends	35,294	0.335	0.472
Cash flow	35,294	0.041	0.120
Cash flow volatility	35,294	0.094	0.045
Net working capital	35,294	0.123	0.178
Acquisitions	35,294	0.021	0.054
Capital expenditure	35,294	0.059	0.062
Panel C: Under-investigated drivers			
R&D spending	35,294	0.031	0.052
Intangible assets	35,294	0.111	0.100
Tangible assets	35,294	0.554	0.392
Tax costs of repatriating earnings	35,294	0.001	0.004
Cost of carry	35,294	0.031	0.021
Debt maturity	35,294	0.443	0.359
Diversification	35,294	2.120	1.466
Relationship with customers	35,294	0.620	0.478
Multinationality	35,294	0.470	0.759

Notes: The table reports means and standard deviations. Variable definitions are provided in Appendix 2.3.

As for Panel C, the statistics for the drivers are generally in line with the previous literature. For instance, the average of the R&D spending is about 3.1% with standard deviation 5.2%, which is comparable with the mean of 4.3% with standard deviation 8.8% reported by He and Wintoki (2016). The tax costs of repatriating earnings of our sample is about 0.001, on average, with standard deviation 0.003. Foley et al. (2007) report the values of 0.001 and 0.0045 as mean and standard deviation in their study. The average fraction of total debt that matures in more than three years is about 44.3% for our sample, which is consistent with Byun et al. (2021).

2.5 Empirical results

2.5.1 Baseline models

As a starting point, Table 2.2 reports the estimation results of a fixed-effects panel data model. We introduce the nine key drivers in subsequent columns after controlling for the standard set of variables used by Opler et al. (1999). In addition, all models include time fixed effects to control for macroeconomic shocks. We report coefficient estimates and *t*-statistics, with standard errors clustered by firm.

Our key firm-level drivers are all statistically significant and support the findings of previous studies. Specifically, we find that R&D expenditures, intangible assets, tax costs of repatriating earnings, debt maturity, relationship with customers and multinationality positively affect cash holdings (Foley et al., 2007; Ramirez and Tadesse, 2009; Duchin, 2010; Itzkowitz, 2013; Harford et al., 2014; He and Wintoki, 2016; Falato et al., 2020). On the other hand, tangible assets and the cost of carry exert a negative and significant effect on cash holdings (Azar et al., 2016; Lei et al., 2018). In summary, we conclude that the main explanatory variables contain information about firms' cash holdings.

Table 2.2 Baseline regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
R&D spending	5.956								
	(38.181***)								
Intangible assets		0.064							
		(3.823***)							
Tangible assets			-4.879						
			(-71.981***)						
Tax costs of repatriating earnings				31.309					
				(17.168***)					
Cost of carry					-18.982				
					(-34.051***)				
Debt maturity						0.475			
						(21.267***)			
Diversification							-0.024		
							(-4.239***)		
Relationship with customers								0.165	
								(10.744***)	
Multinationality									0.540
									(24.418***)
Firm size	0.031	0.044	-0.020	0.028	0.022	0.005	0.046	0.038	-0.032
	(6.905***)	(9.415***)	(-4.947***)	(6.534***)	(5.278***)	(1.141)	(9.685***)	(9.067***)	(-7.030***)
Growth opportunities	0.214	0.284	0.140	0.231	0.246	0.241	0.286	0.244	0.242
	(26.290***)	(34.851***)	(19.904***)	(31.243***)	(33.835***)	(32.734***)	(35.511***)	(33.044***)	(33.395***)
Financial leverage	-3.149	-3.469	-2.471	-3.069	-2.862	-3.351	-3.489	-3.098	-3.260
	(-67.835***)	(-74.138***)	(-60.516***)	(-72.100***)	(-67.162***)	(-76.338***)	(-75.061***)	(-72.695***)	(-75.158***)
Dividends	-0.182	-0.258	-0.115	-0.213	-0.228	-0.220	-0.248	-0.199	-0.205
	(-10.236***)	(-14.320***)	(-7.428***)	(-12.961***)	(-14.028***)	(-13.389***)	(-13.686***)	(-12.058***)	(-12.618***)
Cash flow	0.421	-0.226	0.006	-0.266	-0.087	-0.203	-0.300	-0.187	-0.120
	(6.016***)	(-3.184***)	(0.104)	(-4.217***)	(-1.397)	(-3.236***)	(-4.366***)	(-2.967***)	(-1.939*)
Cash flow volatility	1.232	2.123	0.713	1.750	1.843	1.979	2.205	1.935	1.429
	(6.973***)	(11.816***)	(4.636***)	(10.707***)	(11.432***)	(12.160***)	(12.365***)	(11.833***)	(8.855***)
Net working capital	-2.102	-2.042	-0.428	-1.783	-1.657	-1.922	-2.047	-1.790	-1.884
	(-45.398***)	(-43.243***)	(-9.585***)	(-41.292***)	(-38.708***)	(-44.101***)	(-43.352***)	(-41.347***)	(-43.820***)
Acquisitions	-1.766	-1.893	-3.037	-1.551	-1.627	-1.797	-1.864	-1.601	-1.553
	(-12.950***)	(-13.601***)	(-25.113***)	(-12.189***)	(-12.941***)	(-14.119***)	(-13.399***)	(-12.550***)	(-12.352***)
Capital expenditure	-3.141	-3.325	0.375	-2.929	-2.996	-3.238	-3.508	-3.005	-2.970
	(-25.024***)	(-25.036***)	(3.148***)	(-25.048***)	(-25.957***)	(-27.668***)	(-27.368***)	(-25.663***)	(-25.671***)
Intercept	-1.930	-1.863	-0.058	-2.001	-0.636	-2.035	-1.780	-2.115	-1.995
	(-27.096***)	(-25.283***)	(-0.850)	(-30.087***)	(-8.172***)	(-30.714***)	(-24.353***)	(-31.680***)	(-30.532***)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	35,294	35,294	35,294	35,294	35,294	35,294	35,294	35,294	35,294
R^2_{adj}	0.293	0.264	0.344	0.253	0.271	0.257	0.264	0.250	0.277

Notes: The table reports fixed effects panel regressions. The dependent variable is the log of cash-to-net assets. Robust t-statistics are presented in parentheses. Standard errors are clustered at the firm level. Variable definitions are provided in Appendix 2.3. *, ** and *** denote significance at the 10%, 5% and 1% respectively

2.5.2 The causal effect of the drivers

The results of the baseline regression presented above confirm the strong relation between each of the under-investigated drivers and cash holdings. In this subsection, we estimate the causal effect of each driver on cash holdings, utilizing the double machine learning (DML) approach. By means of the DML procedure, in addition to performing causal analysis, our models do not suffer from the misspecification and the regularization biases of the approaches applied to our problem previously in the literature. Finally, we are able to handle the high dimensional noise in our setting.

We begin our analysis by estimating the causal effect of each driver on its own. Table 2.3 reports the estimates of the separate causal effect corresponding to the nine drivers using the DML procedure over repeated 100 splits. The confounder set consists of twenty-five firm characteristics. Following Yang et al. (2020), we utilize the gradient boosting method to learn the nuisance functions *g* and *m* under two different values for interaction depth, *d=1* and *d=2* in Panels A and B, respectively.[14] The interaction depth controls the order of interactions between covariates. To ensure robustness, we consider two different values for the shrinkage parameter (i.e., *s*, which is also known as the step-size reduction or learning rate): *s*=0.1 (as the default value in the gbm package (Greenwell et al., 2020)), and *s*=0.05. The optimal number of trees is selected by 10-fold cross-validation (CV). Following DeMiguel et al. (2021), we apply standardized variables as a common measure in machine learning application to maintain the estimation process of the ML algorithms scale-invariant.

Table 2.3 Separate causal effects of drivers

Shrinkage parameter	*S*=0.1		*S*=0.05	
Panel A: *d=1*	Effect	t- statistic	Effect	t-statistic
	(1)	(2)	(3)	(4)
R&D spending	0.192	36.660***	0.219	42.070***
Intangible assets	0.033	5.585***	0.063	10.890***
Tangible assets	-0.461	-70.920***	-0.471	-78.360***
Tax costs of repatriating earnings	0.034	5.848***	0.053	8.638***
Cost of carry	-0.142	-26.280***	-0.163	-30.920***
Debt maturity	0.125	21.890***	0.100	17.190***
Diversification	0.004	0.812	0.004	0.845
Relationship with customers	0.048	10.110***	0.063	13.100***
Multinationality	0.145	29.170***	0.170	34.090***
Controls	Yes		Yes	
No. observations	35,294		35,294	
Panel B*: d=2*				
R&D spending	0.175	33.190***	0.193	36.890***

[14] According to James et al. (2013, p. 327), often *d*=1 has good performance, in which case each tree consists of a single split.

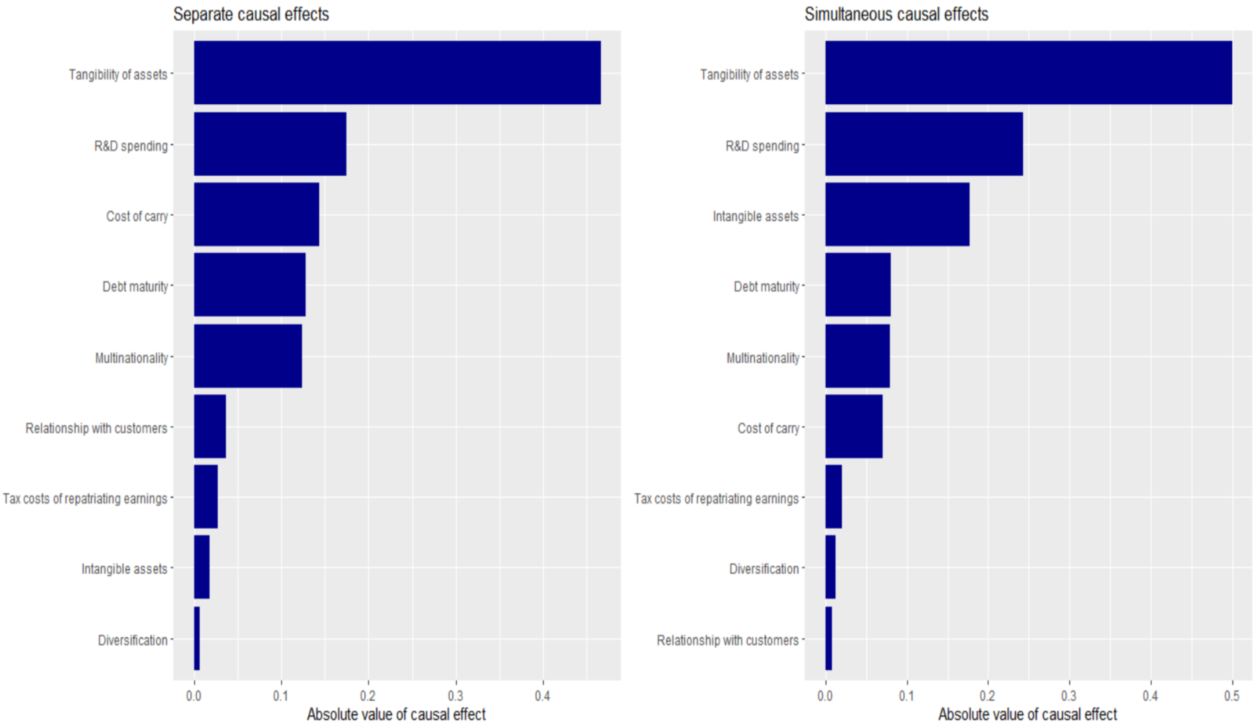
Intangible assets	0.018	2.885***	0.033	5.568***
Tangible assets	-0.466	-65.910***	-0.478	-71.550***
Tax costs of repatriating earnings	0.027	4.471***	0.039	6.418***
Cost of carry	-0.143	-25.130***	-0.151	-27.410***
Debt maturity	0.128	22.740***	0.118	20.520***
Diversification	0.006	1.340	0.004	0.899
Relationship with customers	0.037	7.785***	0.046	9.647***
Multinationality	0.124	24.810***	0.143	28.550***
Controls	Yes		Yes	
No. observations	35,294		35,294	

Notes: The table reports the causal effect of the drivers, one at a time, obtained from double machine learning (DML) utilizing four-fold crossfitting. The nuisance functions (*g* and *m* in Equations (2.1) and (2.2)) are learned with the gradient boosting method under different values of interaction depth (d) and shrinkage (s): (d=1, s=0.1), (1, 0.05), (2, 0.1) and (2, 0.05). The optimal number of trees is selected by 10-fold cross-validation (CV). Estimated effects are based on 100 splits. The dependent variable is the natural logarithm of cash-to-net assets. Variable definitions are provided in Appendix 2.3. *, ** and *** denote significance at the 10%, 5% and 1% respectively.

The DML estimation results show that the individual effects of R&D spending, intangible assets, tax costs of repatriating earnings, debt maturity, relationship with customers and multinationality on cash holdings are positive and statistically significant. By contrast, the tangible assets and cost of carry exert a negative effect on cash holdings. The estimates are negative and statistically significant at the one percent level. In addition, we find that the impact of diversification on cash holdings is insignificant and quantitatively unimportant. Broadly speaking, the observed signs on the separate estimated effects by the DML method, except for multinationality and diversification, are consistent with previous studies which rely to a large extent on traditional regression models (Azar et al., 2016; Falato et al., 2020; Foley et al., 2007; Harford et al., 2014; He and Wintoki, 2016; Itzkowitz, 2013; Lei et al., 2018). To gauge the magnitude of the estimated causal effect, we illustrate the absolute values of the estimated results from the DML procedure under d=2 and s=0.05 in the left panel of Figure 2.1.[15]

[15] The figure remains unchanged for (d=1, s=0.05), (d=1, s=0.1) and (d=2, s=0.0.5). This finding is consistent for the remaining empirical results. To save space, we do not report these figures.

Figure 2.1 Magnitude of causal effects of cash holdings drivers estimated by DML



Note: The figure compares the absolute values of the causal effects of cash holdings drivers separately (left panel) and simultaneously (right panel) obtained by the double machine learning (DML) procedure reported in Table 3 and 4, respectively, corresponding to *d*=2 and *s*=0.05 in the gradient boosting method

We observe that tangible assets has the largest causal effect (in absolute value) on cash holdings. This finding is robust to different values of interaction depth (*d*) and shrinkage parameter (*s*) and highlights the role of collateral in saving cash. The negative effect of tangibles on corporate cash holdings is in line with Lei et al. (2018). According to this study, the upward trend in cash holdings coincides with the decreasing trend in tangibles on balance sheets of US firms. The second largest causal effect is related to R&D expenditures, which underscores the importance of R&D spending for cash management. This supports Begenau and Palazzo (2021), who document that the decline in initial profitability of new lists (the selection mechanism), primarily among R&D-intensive firms, explains about 50% of the upward trend in cash holdings. Finally, the third largest causal effect refers to the cost of carry. In a low-interest-rate environment, firms increase their level of cash, providing a buffer against persistent and transitory cash flow shocks in the future (Zhao, 2020). Conversely, in an environment of high interest rates, external financing is expensive (Lyandres and Palazzo, 2016).

2.5.3 Simultaneous causal effect of the drivers

In this subsection, we estimate the simultaneous causal effect of the under-investigated drivers utilizing the DML method. Here, we consider *all* drivers jointly as target (treatment) variables. In other words, D in Equation (2.2) is a vector of finite dimension containing all drivers rather a scalar variable.[16]

Table 2.4 reports the results. We adjust the *p*-values for multiple hypothesis testing in columns (2) to (4) with step-down methods of Romano and Wolf (2005), Benjamini and Yekutieli (2001) and the Bonferroni correction over 1,000 repetitions.

Table 2.4 Simultaneous causal effects of drivers

	Effect (1)	Romano-Wolf (2)	Benjamini-Yekutieli (3)	Bonferroni (4)
Panel A: *d=1 & s=0.1*				
R&D spending	0.232 (41.512***)	0.000	0.000	0.000
Intangible assets	-0.191 -28.093***)	0.000	0.000	0.000
Tangible assets	-0.472 (-70.787***)	0.000	0.000	0.000
Tax costs of repatriating earnings	0.017 (3.217***)	0.004	0.005	0.012
Cost of carry	-0.060 (-11.605***)	0.000	0.000	0.000
Debt maturity	0.077 (15.335***)	0.000	0.000	0.000
Diversification	-0.014 (-3.182***)	0.004	0.005	0.013
Relationship with customers	0.008 (1.833*)	0.068	0.189	0.601
Multinationality	0.087 (19.101***)	0.000	0.000	0.000
Controls		Yes		
No. observations		35,294		
Panel B: d=2 & s=0.05				
R&D spending	0.243 (42.423***)	0.000	0.000	0.000
Intangible assets	-0.177 (-25.982***)	0.000	0.000	0.000
Tangible assets	-0.500 (-72.748***)	0.000	0.000	0.000
Tax costs of repatriating earnings	0.020 (3.702***)	0.000	0.001	0.002
Cost of carry	-0.070 (-13.431***)	0.000	0.000	0.000
Debt maturity	0.080 (15.861***)	0.000	0.000	0.000
Diversification	-0.013 (-3.030***)	0.005	0.008	0.022
Relationship with customers	0.008 (1.780*)	0.072	0.212	0.675
Multinationality	0.079 (17.660***)	0.000	0.000	0.000
Controls		Yes		
No. observations		35,294		

Notes: The table reports the causal effect of the drivers, simultaneously, obtained from double machine learning (DML) utilizing four-fold crossfitting. The nuisance functions (g and m in Equations (2.1) and (2.2)) are learned with the gradient boosting method

[16] As an additional test, we repeat the analysis by holding one driver constant and placing the remaining drivers in the group of controls. The results, which are available upon request, confirm our main findings. Hence, our methodology is not affected by potential misclassification of the drivers.

under different values of interaction depth (d) and shrinkage (s): (d=1, s=0.1) and (2, 0.05). The optimal number of trees is selected by 10-fold cross-validation (CV). Estimated effects are based on 100 splits. Adjusted *p*-values in columns (2)-(4) for the joint significance tests are based on the multiplier bootstrap procedure (Chernozhukov et al., 2013) in combination with the step-down method of Romano and Wolf (2005), and Benjamini and Yekutieli (2001) and Bonferroni correction over 1,000 repetitions. The dependent variable is the natural logarithm of cash-to-net assets. Variable definitions are provided in Appendix 2.3. *, ** and *** denote significance at the 10%, 5% and 1% respectively

The point estimates in column 1 show that all nine drivers have a strong effect on cash holdings. Based on the adjusted *p*-values obtained from the three correcting methods, the joint causal effects of all drivers, with the only exception being the relationship with customers, remain highly significant. Although, in terms of the step-down procedure of Romano and Wolf (2005), the relationship with customers has a statistically weak effect on cash holdings (Sig.<0.1), this effect is no longer statistically significant based on the other adjusting methods. This finding is robust to different values of interaction depth (*d*) and shrinkage parameter (*s*) of the gradient boosting method in Panels A and B. Particularly, the causal effect of relationship with customers on cash holdings in simultaneous analysis (0.008 in both panels of Table 4) is smaller than the corresponding values in separate analysis (0.048 and 0.046 under the same values of *d* and *s* in Table 3), an approximately 80% weaker impact. In a similar manner with the previous section, the right panel of Figure 2.1 presents the absolute values of the estimated causal effect from our simultaneous analysis.

We can make three main remarks about the magnitudes of the coefficients. First, intangible assets, which were identified as the eight most important drivers in the previous subsection, gain prominence when we pool all variables together. Specifically, the variable is now the third most important factor in explaining cash holdings. This finding suggests that once other firm-level factors are accounted for, the importance of intangible assets becomes more pronounced. As well as identifying a change in the significance of the variable, we also note a switch in the sign. The negative effect of intangible capital on cash holdings is consistent with Marwick et al.’s (2020) postulation, which connects more stable business operation and performance resulting from high organizational capital (as a component of intangible capital in our study) to less of a need for cash reserves.

Second, contrary to considering the firm-level drivers on their own, the DML estimator proves the negative and statistically significant causal effect of diversification on cash holdings. This finding is in line with previous studies (Bakke and Gu, 2017; Duchin, 2010; Fernandes and Gonenc, 2016; Subramaniam et al., 2011). However, consistent with our previously mentioned conjecture, its causal effect is trivial compared to most of the other drivers (0.014 vs. 0.472 of tangible assets in Panel A, for example). The milder effect of diversification on cash holdings compared to multinationality (0.014 vs. 0.087 in Panel A, and 0.013 vs. 0.079 in Panel B) is consistent with Fernandes and Gonenc’s (2016) results regarding the trivial effect of industrial diversification on cash holdings in the presence of multinationality (or global diversification).

Third, tangible assets and R&D expenditures remain the drivers with the first and second largest causal effect on cash holdings. This is robust to different values of interaction depth (d) and shrinkage parameter (s) in Panels A and B. By contrast, 'cost of carry' (as a function of interest rate), has ceded its third place in separate analysis to intangible assets, in simultaneous analysis. Thus, intangible assets have a strong causal effect on cash holdings (0.191 in Panel A and 0.177 in Panel B), while the cost of carry is ranked sixth among the nine drivers, with a small causal effect (0.060 in Panel A and 0.070 in Panel B). This finding leads us to conclude that cost of carry cannot be one of the main causes for the corporate savings glut phenomenon among US industrial firms over 1980-2019. This result is in line with Gao et al.'s (2021) findings that "*interest rates are unlikely to be behind the recent rise in corporate cash* (p. 1834)".

In sum, our separate analysis results indicate that while some of the drivers (e.g., cost of carry and relationship with customers) are economically important to explain the level of cash holdings, they no longer have strong effects on cash holdings in the presence of other drivers. Conversely, some drivers (e.g., intangible assets) that were not individually important in explaining the rise of corporate cash level present themselves as important factors in combination with other drivers. These findings highlight the importance of our simultaneous analysis presented in this section.[17]

2.5.4 Instrumental variable analysis

In the main analysis we assume that that our drivers are exogenous after conditioning on controls X. Although this argument is rooted in the relevant literature, our approach might not alleviate the endogeneity concerns of finance researchers and practitioners. In this section, we combine DML with instrumental variables (hereafter DML-IV) to allay these concerns. Specifically, we instrument the firm-level drivers using their own lagged values.[18] We check for the validity of the instruments using the Sargan test of overidentifying restrictions. In addition, we report the Anderson statistic to test whether the equation is unidentified, which would suggest that the instruments are correlated with the endogenous

[17] Our findings are robust to the selection of the machine learner (LASSO and regression trees) and when we measure cash holdings as the ratio of cash and short-term investment to assets. See Appendix 2.4 and Appendix 2.5.

[18] We have also attempted to instrument the intangible assets with industry median intangible assets, tangible assets with industry median of the ratio of the sales of PP&E to that of total PP&E and capital expenditures. The results, which are available upon request, are robust to this modification.

variables.[19] Both tests are obtained from a linear instrumental variable model and are reported at the foot of the table.

Table 2.5 DML estimation results with instrumental variables

	Effect (1)	Romano-Wolf (2)	Benjamini-Yekutieli (3)	Bonferroni (4)
R&D spending	0.248 (27.236***)	0.000	0.000	0.000
Intangible assets	-0.186 (-6.537***)	0.000	0.000	0.000
Tangible assets	-0.803 (-11.152***)	0.000	0.000	0.000
Tax costs of repatriating earnings	0.068 (2.844***)	0.020	0.019	0.040
Cost of carry	-0.028 (-1.223)	0.478	0.740	1.000
Debt maturity	0.124 (8.673***)	0.000	0.000	0.000
Diversification	-0.009 (-1.194)	0.478	0.740	1.000
Relationship with customers	0.019 (0.999)	0.478	0.899	1.000
Multinationality	0.109 (13.382***)	0.000	0.000	0.000
Controls		Yes		
Anderson statistic		5.648*		
Sargan statistic		0.048		
No. observations		14,405		

Notes: The table reports the causal effect of the drivers, simultaneously, obtained by double machine learning with instrumental variables (DML-IV) utilizing four-fold crossfitting. The nuisance functions (*g* and *m* in Equations (2.1) and (2.2)) are learned with the gradient boosting method with interaction depth (*d*) 1 and shrinkage parameter (*s*) 0.1. The optimal number of trees is selected by 10-fold cross-validation (CV). Estimated effects are based on 100 splits. Adjusted *p*-values in columns (2)-(4) for the joint significance tests are based on the multiplier bootstrap procedure (Chernozhukov et al., 2013) in combination with the step-down method of Romano and Wolf (2005), Benjamini and Yekutieli (2001) and Bonferroni correction over 1,000 repetitions. The Anderson and Sargan test statistics are obtained from a linear instrumental variable model. The Anderson canonical correlation statistic is distributed as chi-square under the null that the equation is unidentified. The Sargan statistic is a test of the overidentifying restrictions, distributed as chi-square under the null of instrument validity. The dependent variable is the natural logarithm of cash-to-net assets. Variable definitions are provided in Appendix 2.3. *, ** and *** denote significance at the 10%, 5% and 1% respectively.

We show the results in Table 2.5 and should be compared with those in Table 4. Specifically, tangible assets with causal effect 0.803 (in absolute value) is still ranked above all drivers. R&D spending is in second place with size of effect 0.248, which is again in line with main findings. A distinctive result is that the cost of carry, one of the less important drivers of the previous sections, is no longer statistically significant. In addition, the Sargan and Anderson tests do not indicate any problems regarding the choice and the relevance of our instruments.

[19] Unreported Partial F-tests suggest that ignoring the defined instruments for each driver reduce the explanatory power of the first-stage regression models. As, the obtained F-statistics are statistically significant, and are much higher than the critical value 10, as a 'rule-of-thumb' measure recommended by Staiger and Stock (1997). Thus, our specifications are not subject to the weak instrument problem.

In sum, we conclude that our findings are robust to controlling for the possible endogeneity of our regressors.

2.5.5 Evolution over time

Next, we explore the evolution of the causal effects over time. In doing so, we can trace how the causal effects change over the years and whether some factors that were previously important to explain the level of cash holdings have lost their importance recently or vice versa. Following He and Wintoki (2016) and Begenau and Palazzo (2021), we split our sample into five-year windows. We report the estimates for different time periods in Table 2.6. In addition, we depict the time series plot of the related magnitude of the causal effects in Figure 2.2.

The cross-sectional estimation of simultaneous causal effect reveals some interesting results. First, the magnitude of R&D expenditures, multinationality and intangible assets improves over the years, indicating the growing importance of these factors to explain the level of corporate cash holdings. Among these, we note the largest increase for intangible assets: starting the sample period with a trivial absolute value of 0.003 and ending it with 0.287 (about 96 times higher). The increasing sensitivity of cash holdings to intangible assets is consistent with the significant growth of these assets in the balance sheet of US firms (Lei et al., 2018), as well as the apparent shift from tangible towards intangible capital in assets composition (Denis and McKeon, 2021; Falato et al., 2020). The causal effect of R&D expenditures on cash holdings is also considerably higher over the years. Specifically, in the first five-year period (1980-1984), the causal effect of R&D expenditures is 0.029 and statistically insignificant (t=1.638). During the last five-year period (2015-2019), it attains the highest value of 0.311 (about 11 times higher). Multinationality exhibits a different pattern of effect on cash holdings over the last two subperiods. After reaching a peak of 0.134 during 2005-2009, the simultaneous causal effect of multinationality on cash holdings reduces to 0.093 and then 0.062 over 2010-2014 and 2015-2019, respectively.[20]

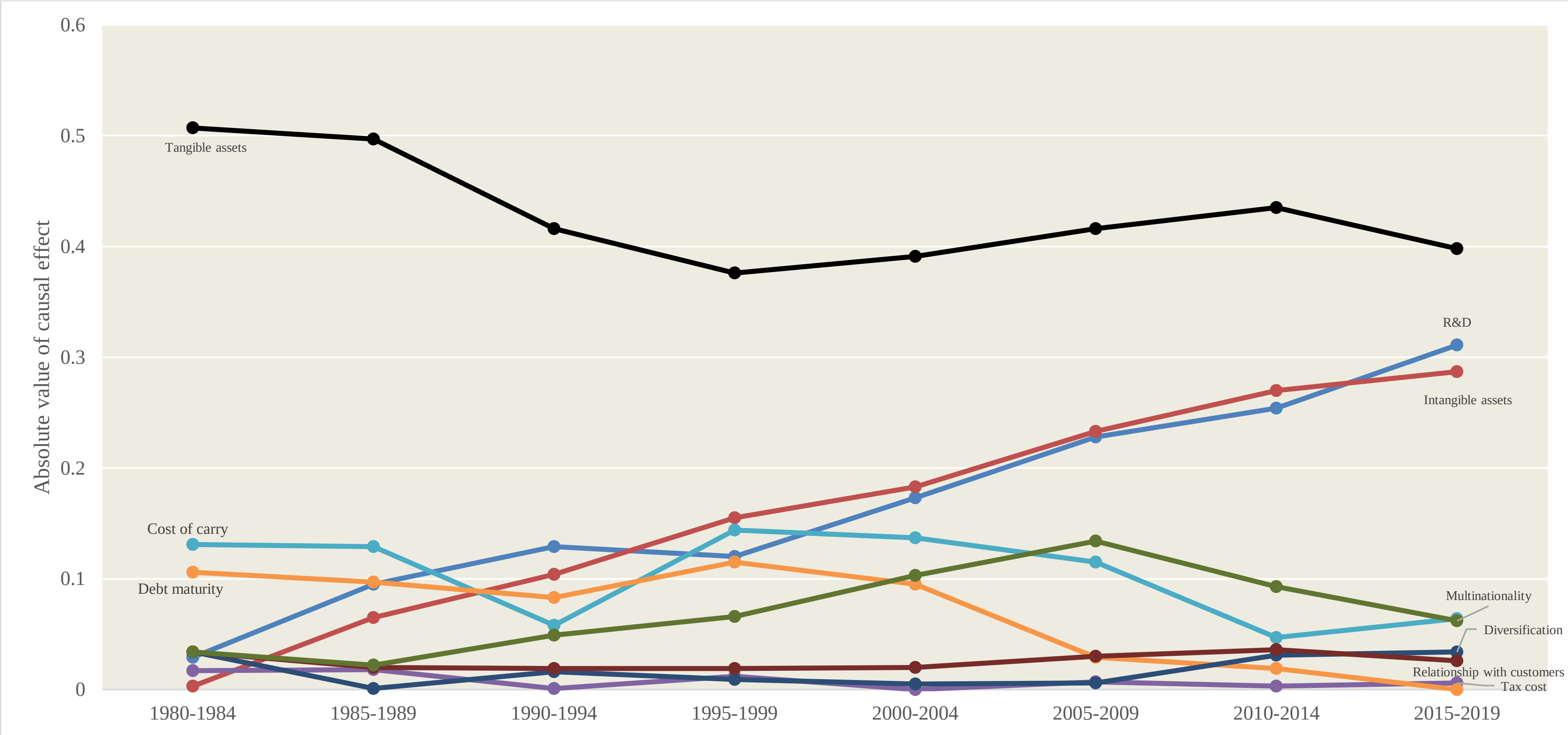
[20] When we consider the drivers independently of each other, R&D expenditures still show an upward trend of causal effect on cash holdings. By contrast, the observed pattern on intangible assets' causal effect substantially changes, such that it does not have a definite pattern and fluctuates between positive and negative values, with the largest value (i.e., 0.053) over 1990-1994.

Table 2.6 Simultaneous causal effects of the drivers over time

	1980-1984	1985-1989	1990-1994	1995-1999	2000-2004	2005-2009	2010-2014	2015-2019
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R&D spending	0.029 (1.638)	0.095 (5.392***)	0.129 (7.298***)	0.120 (7.831***)	0.173 (11.923***)	0.228 (15.183***)	0.254 (16.606***)	0.311 (18.515***)
Intangible assets	-0.003 (-0.171)	-0.065 (-3.143***)	-0.104 (-5.298***)	-0.155 (-8.400***)	-0.183 (-10.815***)	-0.233 (-12.156***)	-0.270 (-13.963***)	-0.287 (-13.939***)
Tangible assets	-0.507 (-24.289***)	-0.497 (-24.939***)	-0.416 (-20.685***)	-0.376 (-21.754***)	-0.391 (-23.186***)	-0.416 (-25.184***)	-0.435 (-26.077***)	-0.398 (-20.893***)
Tax costs of repatriating earnings	0.017 (1.221)	0.018 (1.308)	-0.001 (-0.076)	0.012 (0.873)	0.000 (0.033)	0.007 (0.521)	-0.003 (-0.168)	-0.006 (-0.381)
Cost of carry	-0.131 (-8.816***)	-0.129 (-8.508***)	-0.058 (-4.187***)	-0.144 (-13.271***)	-0.137 (-10.659***)	-0.115 (-9.340***)	-0.047 (-4.239***)	-0.064 (-5.195***)
Debt maturity	0.106 (6.879***)	0.097 (6.850***)	0.083 (5.803***)	0.115 (8.221***)	0.095 (7.658***)	0.029 (2.247**)	-0.019 (-1.321)	-0.000 (-0.019)
Diversification	-0.034 (-2.449**)	0.001 (0.105)	-0.016 (-1.263)	-0.009 (-0.753)	0.005 (0.439)	-0.006 (-0.546)	-0.031 (-2.807***)	-0.034 (-2.804***)
Relationship with customers	0.034 (2.488**)	0.020 (1.477)	0.019 (1.425)	-0.019 (-1.576)	0.020 (1.961**)	0.030 (2.899***)	0.036 (3.414***)	0.026 (2.420**)
Multinationality	0.034 (2.639***)	0.022 (1.334)	0.049 (2.589***)	0.066 (5.836***)	0.103 (9.123***)	0.134 (12.109***)	0.093 (8.411***)	0.062 (5.295***)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. observation	2,943	3,547	3,725	4,259	4,822	5,495	5,392	5,111

Notes: This table presents the DML estimation of simultaneous causal effect of the drivers on cash holdings for the following five-year periods 1980-1984, 1985-1989, 1990-1994, 1995-1999, 2000-2004, 2005-2009, 2010-2014 and 2015-2019. The dependent variable is the natural logarithm of cash-to-net assets. The nuisance functions (*g* and *m* in Equations (2.1) and (2.2)) are learned with the gradient boosting method with 1 and 0.1 for interaction depth (*d*) and shrinkage parameter (*s*), respectively, within four-fold crossfitting. The optimal number of trees is selected by 10-fold cross-validation (CV). Estimated effects are based on 100 splits. Variable definitions are provided in Appendix 2.3. *, ** and *** denote significance at the 10%, 5% and 1% respectively

Figure 2.2 Time series plot of the simultaneous causal effect estimation of drivers



Note: This figure illustrates the time series plot of the estimated simultaneous causal effect of the drivers on cash holdings using the DML method for eight five-year periods (1980-1984, 1985-1989, 1990-1994, 1995-1999, 2000-2004, 2005-2009, 2010-2014 and 2015-2019), reported in Table 5

Second, the magnitude for debt maturity, tangible assets and cost of carry drops over the later part of the sample period. In particular, the largest decrease belongs to debt maturity: starting the sample period with highly significant causal effect 0.106 (t=6.879, Sig.<0.01) and becoming statistically insignificant at the last time window. The downward trend of the causal effect of debt maturity on cash holdings can be explained by the secular increase in debt maturity recently reported by Byun et al. (2021).[21] As for tangible assets, the diminishing importance in the magnitude coincides with the substantial decline in asset tangibility among US firms, starting from around 1980 (Lei et al., 2018,). Finally, the magnitude for the cost of carry drops from 0.131 in 1980-1984 to 0.064 in the last time window. The diminishing importance of the cost of carry, as a function of interest rate, is justifiable by the fact that adoption of electronic payment technologies reduces the cost and time required to convert interest-bearing assets into cash needed for transaction purposes (Azar et al., 2016).

Third, due to their trivial effects on cash holdings, relationship with customers, tax cost of repatriating earnings and diversification fluctuate between negative and positive causal effects across the periods. For instance, the DML estimation of diversification's causal effect was highly significant (-0.034, Sig<0.01) during the first five-year period (1980-1984). This effect turned to be statistically insignificant over the four subsequent periods (i.e., from 1985-1989 to 2000-2004).

In sum, based on the cross-sectional estimations results, we introduce R&D expenditures, tangible assets, intangible assets, cost of carry and multinationality as *stable* drivers behind the upward trend in cash savings, in Graham and Leary's (2018) terminology, as these factors display both stable sign and significance on their causal effects. In this sense, tax costs of repatriating earnings, debt maturity, diversification and relationship with customers cannot be considered as stable determinants of cash holdings.

2.5.6 The role of the global financial crisis

Armed with the findings of the previous sub-section, we delve deeper to examine whether the importance of the drivers differs between crisis and noncrisis times. There is evidence that the global financial crisis of 2008 drastically changed corporate policies, including liquidity management, among US firms (e.g., Campello et al., 2011, 2010). We analyse the sensitivity of cash holdings to the drivers by considering three periods: pre-crisis (1980-

[21] In fact, Custódio et al. (2013) and Harford et al. (2014) document that the maturity of US firms' long-term debt has shortened over 1980-2008. By contrast, Byun et al. (2021) report a secular increase in debt maturity by updating the spanning period from 1976 to 2017.

2006), crisis (2007-2008) and post-crisis (2009-2019). Table 2.7 presents the related results. The absolute values of the paired sample *t*-test to test the differences of causal effects between each pair of periods are reported in the last three columns.

Table 2.7 Simultaneous causal effects of the drivers before, during and after financial crisis

	Pre crisis (1980-2006)	During crisis (2007-2008)	Post crisis (2009-2019)	Difference of effects		
	(1)	(2)	(3)	(1)-(2)	(1)-(3)	(2)-(3)
R&D spending	0.189 (27.258***)	0.212 (8.957***)	0.291 (27.338***)	6.44***	90.10***	20.20***
Intangible assets	-0.150 (-18.179***)	-0.248 (-8.422***)	-0.281 (-21.111***)	66.40***	147.00***	23.30***
Tangible assets	-0.444 (-53.413***)	-0.425 (-16.441***)	-0.428 (-37.003***)	4.94**	9.21***	0.31
Tax costs of repatriating earnings	0.020 (3.436***)	-0.011 (-0.523)	0.005 (0.461)	18.20***	29.90***	10.60***
Cost of carry	-0.067 (-11.542***)	-0.096 (-5.056***)	-0.055 (-6.990***)	13.30***	15.70***	31.50***
Debt maturity	0.119 (19.341***)	0.027 (1.309)	-0.009 (-0.940)	42.60***	137.00***	12.20***
Diversification	0.000 (0.029)	-0.025 (-1.399)	-0.034 (-4.426***)	20.40***	75.80***	0.16
Relationship with customers	-0.007 (-1.358)	0.019 (1.196)	0.033 (4.566***)	9.01***	137.00***	8.65***
Multinationality	0.085 (14.907***)	0.119 (6.976***)	0.090 (11.766***)	19.20***	11.20***	16.70***
Controls	Yes	Yes	Yes			
N. observations	21,463	2,212	11,619			

Note: The table compares the simultaneous causal effect of the drivers among pre-crisis (1980-2006), during crisis (2007-2008) and post-crisis (2009-2019). Estimated effects are from double machine learning (DML) utilizing four-fold crossfitting. The nuisance functions (*g* and *m* in Equations (2.1) and (2.2)) are learned with the gradient boosting method with interaction depth (*d*) 1 and shrinkage parameter (*s*) 0.1. The optimal number of trees is selected by 10-fold cross-validation (CV). Estimated effects are based on the 100 splits. The absolute values of the paired sample *t*-test to test the differences of causal effects between each pair of periods are reported in the last three columns. Variable definitions are provided in Appendix 2.3. *, ** and *** denote significance at the 10%, 5% and 1% respectively.

The first insight from the table is that the empirical relation between cash holdings and each of the nine drivers significantly changed during the financial crisis. In particular, tests of equality suggest that the magnitude of causal effects in the midst of the financial crisis (2007-2008) are statistically different from the corresponding effects in the pre-crisis (1980-2006) and post-crisis (2009-2019) periods. Second, for some drivers (such as R&D spending and intangible assets) the causal effect has increased (in absolute value) in the post-crisis era relative to the pre-crisis times. Overall, we conclude that the sensitivity of cash holdings to firm-levels drivers is significantly different during extreme economic events compared to calmer periods.

2.5.7 Heterogeneity at the industry level

There is ample evidence that the spike in cash reserves is an industry-related phenomenon. For example, He and Wintoki (2016) show that the secular upward trend in cash-to-assets ratio is only related to innovative industries. Booth and Zhou (2013) report that the cash ratio of high-tech industries more than tripled between 1980 and 2007, while the ratio remained almost stable for other industries. Recently, Graham and Leary (2018), and with more detail Li and Luo (2020), document that healthcare industries, along with technology industries, are only the sectors that have significantly increased their cash holdings (for a comparison of cash-to-assets ratio time series between health/tech industries and other ones in our sample, see Appendix 2.8). Motivated by these considerations, we hypothesize that heterogeneity is prevalent at the industry level.

To test our hypothesis, we split our sample into two groups: healthcare and technology industries, and other industries, based on the Fama-French 12-industry classification, following Graham and Leary (2018).[22] Some of the industries in the health/tech group are pharmaceutical, office and computing equipment, communications, scientific instruments, software, medical and dental instruments, etc. Table 2.8 reports the DML estimation of simultaneous causal effect of drivers for the two sectoral groups.

The results strongly suggest that eight of the nine drivers make a remarkable contribution in describing the phenomenon of cash increase in the health/tech industrial group. To compare the effect size of the nine drivers between health/tech industries and other industries, we depict the absolute values of the estimated causal effects of drivers in Figure 2.3. In line with the main findings based on the full sample, tangible assets and R&D expenditures are among the top factors affecting cash holdings in both sectors. This finding indicates that apart from the sector in which the company operates, tangible assets and R&D spending are the two main forces for running up in cash holdings among US industrial firms over the sample period (1980-2019). This is robust to different values for hyperparameters of gradient boosting (i.e., d and s) in nuisance function estimation. In summary, we find that our main findings hold when we split the firms into different industrial groups.

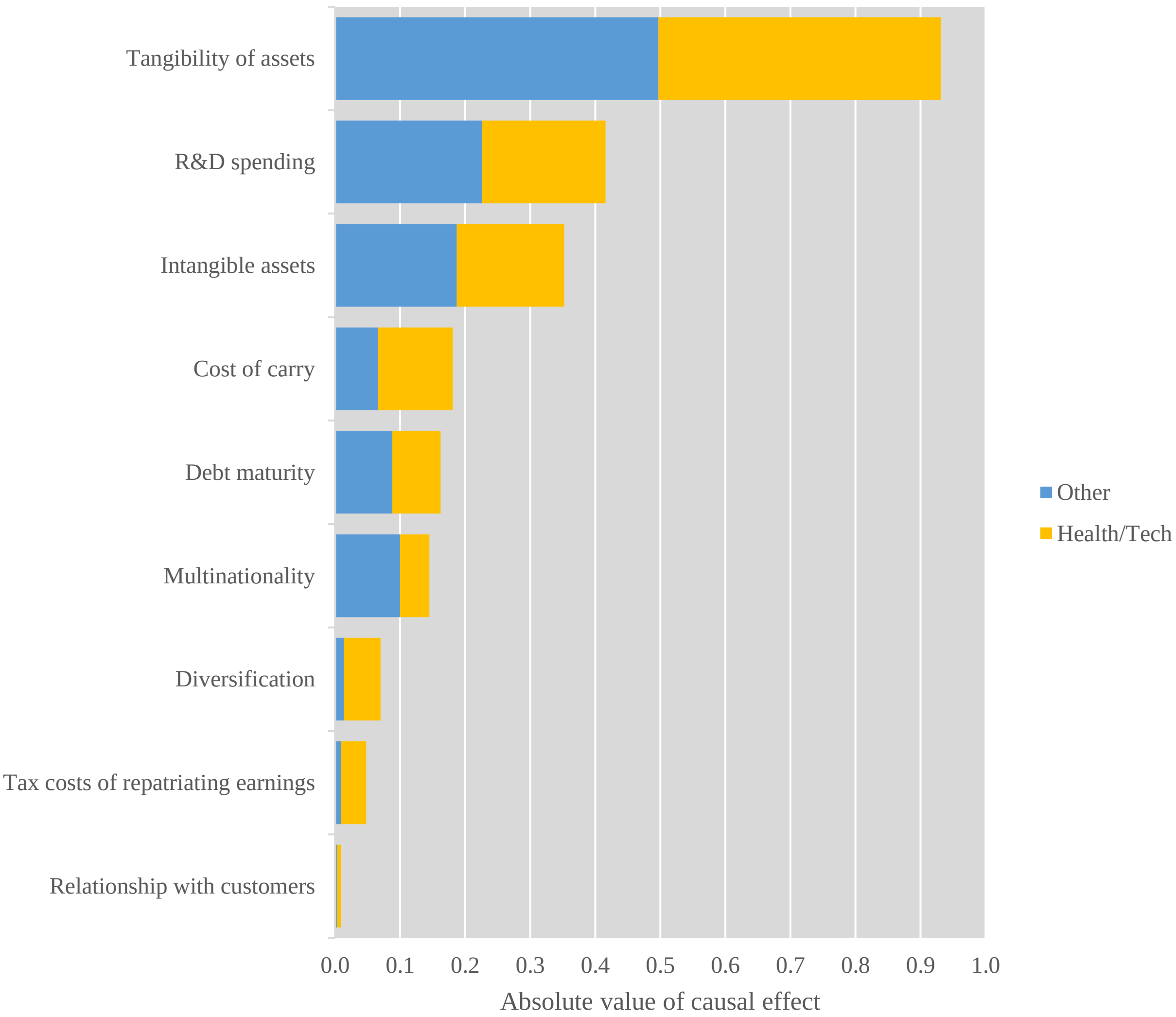
[22] The Fama-French 12-industry classification is available on Kenneth French's web page at Dartmouth (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library/det_12_ind_port.html).

Table 2.8 Simultaneous causal effects of the drivers by industry

Industry	Health & Technology Industries				Other industries				
	Effect (1)	Romano-Wolf (2)	Benjamini-Yekutieli (3)	Bonferroni (4)	Effect (5)	Romano-Wolf (6)	Benjamini-Yekutieli (7)	Bonferroni (8)	Difference of effects (1)-(5)
Panel A: *d=1 & s=0.1*									
R&D spending	0.187	0.000	0.000	0.000	0.222	0.000	0.000	0.000	144.270***
Intangible assets	-0.166	0.000	0.000	0.000	-0.199	0.000	0.000	0.000	102.400***
Tangible assets	-0.421	0.000	0.000	0.000	-0.465	0.000	0.000	0.000	135.590***
Tax costs of repatriating earnings	0.034	0.000	0.000	0.000	-0.011	0.203	0.345	0.974	224.360***
Cost of carry	-0.108	0.000	0.000	0.000	-0.060	0.000	0.000	0.000	184.430***
Debt maturity	0.072	0.000	0.000	0.000	0.085	0.000	0.000	0.000	70.384***
Diversification	-0.051	0.000	0.000	0.000	0.012	0.057	0.070	0.172	432.170***
Relationship with customers	0.009	0.190	0.534	1.000	-0.007	0.203	0.562	1.000	106.600***
Multinationality	0.046	0.000	0.000	0.000	0.107	0.000	0.000	0.000	321.770***
Controls			Yes					Yes	
N. observations			10,412					24,882	
Panel B: d=2 & s=0.05									
R&D spending	0.190	0.000	0.000	0.000	0.226	0.000	0.000	0.000	146.170***
Intangible assets	-0.165	0.000	0.000	0.000	-0.187	0.000	0.000	0.000	94.957***
Tangible assets	-0.434	0.000	0.000	0.000	-0.497	0.000	0.000	0.000	172.720***
Tax costs of repatriating earnings	0.039	0.000	0.000	0.000	-0.009	0.406	0.727	1.000	231.170***
Cost of carry	-0.115	0.000	0.000	0.000	-0.066	0.000	0.000	0.000	137.480***
Debt maturity	0.074	0.000	0.000	0.000	0.088	0.000	0.000	0.000	77.424***
Diversification	-0.056	0.000	0.000	0.000	0.014	0.028	0.035	0.086	447.770***
Relationship with customers	0.006	0.348	0.985	1.000	-0.003	0.534	1.000	1.000	80.628***
Multinationality	0.045	0.000	0.000	0.000	0.100	0.000	0.000	0.000	194.540***
Controls			Yes					Yes	
N. observations			10,412					24,882	

Note: The table reports the estimated causal effects of the drivers simultaneously, by two sectors: healthcare and technology industries and other industries. Industry classification is based on the Fama-French 12-industries. Estimated effects are from double machine learning (DML) utilizing four-fold crossfitting. The nuisance functions (g and m in Equations (2.1) and (2.2)) are learned with the gradient boosting method under different values of interaction depth (d) and shrinkage (s): (d=1, s=0.1) and (2, 0.05). The optimal number of trees is selected by 10-fold cross-validation (CV). Estimated effects are based on the 100 splits. Adjusted p-values for the joint significance tests are based on the multiplier bootstrap procedure (Chernozhukov et al., 2013) in combination with step-down method of Romano and Wolf (2005), and Benjamini and Yekutieli (2001) and Bonferroni correction over 1,000 repetitions. The absolute values of the Student's t statistic to test the differences of causal effects between two sectors are reported in the last column. Variable definitions are provided in Appendix 2.3. *, ** and *** denote significance at the 10%, 5% and 1% respectively.

Figure 2.3 Magnitude of simultaneous causal effects of drivers by industry



Note: The figure compares the absolute values of the simultaneous causal effects of the drivers between two sectors: healthcare and technology industries and other industries. The estimated effects are based on the DML procedure under *d*=2 and *s*=0.05.

2.6 Implications

The implications drawn from this chapter are twofold. Firs, findings demonstrate that certain variables, deemed potential contributors to the cash puzzle, exert a significant impact on cash holdings when analysed individually. However, their significance diminishes in the context of simultaneous analysis, which aligns more closely with real-world scenarios where multiple factors come into play concurrently. This holds crucial implication for academic research, emphasizing the importance of accounting for the influence of other drivers when investigating the impact of a novel factor in future studies. It underscores the need for a holistic approach that considers the hidden interactions of various factors in explaining the phenomenon. In the context of simultaneous analysis involving multiple factors, a critical consideration is the adjustment of p-values to mitigate data snooping bias and prevent false discoveries arising from multiple hypothesis testing. This precaution is essential to maintain the integrity and reliability of the statistical inferences, ensuring that the significance levels accurately reflect the true impact of the *new* variable under investigation, rather than being inflated due to the exploration of numerous hypotheses simultaneously.

Second, the findings strongly suggest that the tangible assets plays a crucial role in driving the increase in cash reserves among U.S. industrial firms. Beyond its academic significance, this revelation holds profound implications for policymakers, shedding light on what might be one of the primary factors contributing to the sluggish recovery from the Great Recession. As highlighted by Sánchez and Yurdagul (2013) in a paper published by the Federal Reserve: "*U.S. corporations are holding record-high amounts of cash. Understanding this phenomenon, many argue, may help us tease out the reasons for the slow recovery from the Great Recession*". The decreasing trend of tangible assets on the balance sheets of U.S. firms, coupled with a shift towards intangibles since the late 1970s, has compelled companies to divert resources from investment to accumulate precautionary savings. This shift is anticipated to impede economic growth since corporate investment, often reliant on financing based on tangible assets (Lei et al., 2018 and Chaney et al., 2012).

2.7 Conclusion

This chapter examines with DML the drivers that impact firms' accumulation of cash, focusing on the US over a long time period. Relative to the methods employed by the previous related literature, DML deals with multicollinearity, nonlinearity and the omitted variable bias. Consequently, it allows us to estimate accurately the casual effect of the determinants of firms' cash holdings on a multi-dimensional setting.

Our results offer several interesting insights. First, we show that financial factors contain information about firms' cash holdings, confirming earlier findings in the literature. This result is obtained using a simple panel data model and more advanced machine learning techniques. Second, we note that the significance of the firm-level drivers varies when they are considered independently and jointly, pointing to the issue of multicollinearity and omitted variable bias which plagues the literature. Third, the magnitude of the drivers evolves over the years, suggesting that some factors gain importance while others diminish. We also uncover significant heterogeneity at the industry level, which shows that not all firm-level drivers are important for firms' cash accumulation. More specifically, we reveal the causes behind the increase of R&D and high-tech firms' cash holdings over the last three decades. This is an important finding because technological differences influence the response of cash holdings to changes in financial indicators.

Our study reveals that the relationship between cash holdings and financial ratios is complex and dynamic. DML assists us in revealing this relationship and in highlighting the time-varying importance of the variables that the literature suggests as drivers on cash holdings. Our results reveal a parsimonious set of predictors on cash holdings (R&D expenditures, tangible assets, intangible assets, cost of carry and multinationality) that can be readily implemented by investors, policy makers and managers. At the same time, we uncover that some variables that the previous literature suggests have a causal effect relationship with cash holdings (tax costs of repatriating earnings, debt maturity, diversification and relationship with customers) should be treated with skepticism.

Chapter 3: Double machine learning and M&A returns determinants

3.1 Introduction

M&A deals stand as pivotal events in a company's lifecycle, exerting a profound influence on the firm's operations and activities like empowering firms to swiftly penetrate new markets, cross-selling to a broader customer base, broadening their scope by acquiring complementary products, etc. (Renneboog and Vansteenkiste, 2019). The magnitude of transactions in such deals is often so substantial that, in certain instances, it may surpass the entire GDP of a country. For instance, the 2016 deal between the German pharmaceutical company Bayer and the US-based Monsanto was valued at $66 billion. Bayer secured this deal with an enhanced bid, surpassing the GDP of Luxembourg in 2015, which stood at $57.8 billion.[23]

Martynova and Renneboog (2008) contend that no singular theory is sufficient to explain M&A activity. This is attributed to the intricate nature of takeover motives (Piesse et al., 2022). While not mutually exclusive or exhaustive, the prevalent theories used to explain M&A activities include agency theory, free cash flow, market power hypothesis, and efficiency theory (Devos et al., 2009; King et al., 2021; Piesse et al., 2022).[24]

In accordance with agency theory (Jensen and Meckling, 1976), management compensation contracts are designed to mitigate managerial opportunism by aligning the interests of management with those of shareholders. An effective strategy for achieving this alignment involves tying management compensation to firm performance, often through the implementation of equity-based compensation structures. The premise is that if the proportion of compensation linked to equity is sufficiently high, managers would be dissuaded from making suboptimal acquisitions due to the potential negative impact on their long-term wealth (Renneboog and Vansteenkiste, 2019). Shleifer and Vishny (1991) highlights the significant influence of personal objectives of corporate managers, emphasizing them as a primary factor contributing to the initiation of the third merger wave

[23] Reuters, Sep. 15th, 2016. http://www.reuters.com/article/us-monsanto-m-a-bayer-deal-idUSKCN11K128.

[24] King et al. (2021) classify M&A theories into three groups based on different phases: pre-acquisition (e.g., agency theory), completion (e.g., portfolio theory), and post-acquisition (e.g., coordination theory).

(1950s-1973), as prior to the 1980s managers had insufficient incentives to focus on shareholder concerns.

The free cash flow hypothesis is closely associated with agency theory. Free cash flow is defined as "*cash flow in excess of that required to fund all projects that have positive net present values when discounted at the relevant cost of capital* (Jensen 1986, p. 323)." The free cash flow hypothesis suggests that self-interested managers may utilize these funds (free cash flows) for 'empire building' rather than returning them to shareholders. The presence of excess cash enables managers to engage in suboptimal acquisitions when superior opportunities are scarce (Martynova and Renneboog, 2008). Numerous empirical studies support this notion, indicating that acquiring firms with surplus cash flows often erode value by overbidding (e.g., Harford, 1999, and Lang et al, 1991).

Market power and efficiency theory are two additional prevalent theories in the literature used to elucidate M&A activities. Market power can be understood as a firm's capacity to influence the quality, pricing, and supply of its products. Given that takeovers offer swift growth opportunities for a company, they can be perceived as a strategic approach to expanding control over a broader geographical area and enlarging the trading environment (Piesse et al., 2022). In fact, market power is one of the three main reasons for horizontal acquisition (defined as acquisitions between firms belonging to the same industry (Capron, 1999)) listed by Shahrur (2005). The efficiency theory proposes that if firm A is more efficient than firm B and both operate in the same industry, a takeover by A can enhance B's efficiency, bringing it up to at least the level of A (Piesse et al., 2022). It is well-known that the merger waves of the 1990s were predominantly driven by the pursuit of enhanced efficiency within the industry (Cumming et al., 2023). The empirical analysis conducted by Devos et al. (2009) reveals that the benefits derived from M&A activity primarily stem from efficiency improvements, with a minor contribution from tax savings, rather than being driven by market power. Similarly, Shahrur (2005) fail to find evidence that mergers lead to market power. Healy et al. (1992) find that operating performance improves after a merger.

A great deal of effort has been made in literature to identify the determinants of merger performance. Some of these determinants can be treated as benchmark variables (e.g., status of the target, deal attitude, bidder and target advisors) because they are used by default in the merger and acquisition (M&As) returns prediction model by most researchers. Beyond the commonly used variables, several factors are proposed in literature as potential determinant of merger performance. But there is still an unanswered question: *Which* *variables, beyond the commonly used ones, hold crucial information for predicting announcement returns?*

In this study, we try to answer the above question by a new machine learning method, i.e., double (or debiased) machine learning (DML) of Chernozhukov et al. (2017, 2018). We have two main reasons to adopt the DML as the desired econometrics method in this study. First, given the extensive factors influencing the M&A returns, we are facing a high-dimensional problem. Traditional ML methods like LASSO, which are originally developed for high-dimensional problems, are associated with the so-called 'omitted variables bias'. Meaning that it is possible that some of the relevant predictors with important information content for M&A returns are not selected in one-step usage of variable selection methods, due to model selection mistake. Owing to double usage of machine learners in the step of nuisance function estimation, the DML estimator does not suffer from this biasedness. This is exactly the main reason that Feng et al. (2020) utilize the double selection (DS) method of Belloni et al. (2014), to 'taming the factor zoo'. The DS is an older version of DML which is based on the linearity assumption.

Second, nonlinear and complex nature of the relationship between predictors and M&A returns may cause generating spurious findings from OLS or traditional ML methods which are based on the linearity assumption. There is ample evidence regarding the nonlinear relation between acquisition performance and its determinants. For example, Hubbard and Palia (1995) show that merger performance nonlinearly changes with ownership structure. Massa and Xu (2013) consider the quadratic effect of firm size in their statistical specifications.[25] Therefore, it can be argued that making inference on the relative importance of M&A return determinants requires econometrics method that assume possible nonlinear structures of association between predictors and outcome. In DML, one can use efficient ML methods to account for these possible nonlinearities. Following Yang et al. (2020), we combine DML with gradient boosting method (GBM) of Friedman (2001). As a tree-based methods, GBM outperforms standard approaches in dealing with nonlinearities between the features and the response (James et al., 2013, p. 319).

In addition to the two reasons discussed above, DML estimator have some desirable features which make it attractive for our purpose. As we will discuss later, by exploiting the orthogonalization technique, DML obviates the regularization bias associated with the naïve

[25] To highlight the relevance of accounting for nonlinearity between predictors and cumulative abnormal returns, as the proxy for merger performance, we illustrate the marginal relations for some of the selected characteristics using P-spline smoothing technique in Appendix 3.1.

estimator (Chernozhukov et al., 2018). It also generates an unbiased, approximately normally distributed, and consistent estimator for the parameter of interest (Chernozhukov et al., 2018).

In this study, we utilize the DML algorithm to investigate the informational value of M&A short abnormal return determinants that go beyond the commonly-used factors. For this purpose, we follow Feng et al. (2020) and employ a forward stepwise procedure. To eleborate, we start with a small set of predictors (seven) as benchmarks based on prior knowledge of researcher. Then, we recursively evaluate the contribution of forty-two additional predictors, thematically categorized, against these benchmarks. Following Bonaime et al. (2018) and Moeller et al. (2007), we employ cumulative abnormal returns (CAR) within one day around the announcement date (3-day CAR) as the primay measure for M&A outcome. For robustness check, we repeat the DML analysis using 8-day CAR.

Using a sample of US acquisitions over 1986-2019, we find strong evidence regarding the prevalence of irrelevant predictors in M&A literature. Meaning that, the DML procedure reveals a sparse set of variables that play a significant role in predicting M&A returns. Specifically, the analysis identifies only five (eight) predictors for $CAR(-1,1)$ ($CAR(-4,4)$) that exhibit statistically significant effects.

We find predominant role for information-related variables in predicting short-run announcement returns. More precisely, variables with significant effects on $CAR(-1,1)$ are: target's number of analysts, target advisors, bidder advisors, high-tech deal indicator, and transaction value. Among these, the first three variables are intricately linked to the flow of information in merger transactions, and they are frequently scrutinized from this perspective in existing literature (e.g., Chemmanur et al., 2009; Golubov et al., 2012; Servaes and Zenner; 1996). Additionally, high-tech deal indicator is closely related to the issue of information asymmetry due to the nature of intangible assets embedded in high-tech industries (e.g., Benou et al., 2007).

Concerning $CAR(-4,4)$, besides the aforementioned information-related variables, macro-level predictors emerge as noteworthy determinants. Particularly, DML introduces market valuations of Bouwman et al. (2009) and geopolitical risk of Hao et al. (2022) with significant effects on merger performance.

To substantiate our findings, we undertake a battery of robustness analyses. First, we substitute the prior knowledge-based benchmarks with the random ones and repeat the DML analysis over 100 permutations. Second, we utilize alternative machine learners (LASSO, regression trees) to estimate nuisance functions in the first step of DML analysis. The obtained results qualitatively support our main findings.

This study has three major contributions to M&A literature. First, we show that the majority of explanatory variables introduced in literature do not provide information content for merger performance prediction beyond those variables that consistently appear in extant empirical research. This underscores the importance of formulating novel theories to identify potential predictors that elucidate M&A returns, as discussed in the work of King et al. (2004).

Second, our study is firmly built on the solid groundwork laid by Moeller et al. (2007) and Servaes and Zenner (1996). We document that variables that are assumed to mitigate information asymmetry play an important role in predicting M&A announcement period returns. Although unlike Moeller et al.'s (2007) research we do not find a significant effect for the long-term earnings growth forecasts (LGT), but our findings illustrate that another related variable, that is, the number of analysts, is of great importance for predicting CARs. Additionally, our results confirm the significant effect of investment advisors for bidder and target, consistent with Servaes and Zenner (1996).

Third, we create a reliable benchmark for future research. Our findings suggest that variables such as target's number of analysts, target advisors, and bidder advisors should be used as benchmarks along with commonly-used variables, for evaluating the impact of new predictors in future studies that aim to explain M&A returns. These variables have shown consistent contributions in our analysis and can serve as valuable reference points in similar research endeavours.

Our study is related to a strand of literature in accounting and finance which utilize DML procedure to identify significant effects on an underlying process. Hansen and Siggaard (2023) utilize the DML method to identify the most important determinants of post-earnings announcement drift. Yang et al. (2020) study the Big N audit quality effect in accounting literature by this method. We extend the application of DML into the realm of M&As. In this way, we further diversify the portfolio of machine learning techniques previously used in the M&A literature (e.g., Liu et al., 2022; Wiedemann and Niederreiter, 2021; Yang et al., 2014).

The rest of the chapter is organized as follows. We review the relevant studies in Section 2. Section 3 describes our sample and the M&A return determinants used in the empirical analysis. Section 4 introduces the DML technique. Section 5 presents the results. Section 6 concludes the chapter.

3.2 Literature review

3.2.1 Determinants of M&A returns

To explain merger performance, different factors and determinants are proposed by authors in literature, from acquirer, deal, and target-specific factors to industry and macro-level ones. In this section, we review those determinants which are considered in our empirical analysis. For a recent comprehensive review on M&A literature, we refer to Cumming et al. (2023), Mulherin et al. (2017) and Renneboog and Vansteenkiste (2019).[26]

3.2.1.1 Acquirer, deal, and target-specific factors

Some of the most commonly used factors in this group are status of the target (public vs. private), structure of the bidder (diversified vs non-diversified), method of payment (cash, stock, or mixed), bidder and target advisors, deal attitude (friendly vs. hostile), type of acquisition (tender vs. merger), etc.

Travlos (1987) reports a significant difference in the abnormal returns between stock and cash offers. He concludes that failing to control for the effect of method of payment may lead to misleading findings in M&A literature. Regarding the structure of bidder, i.e., whether the bidder and target operate in the same industry, Amihud and Lev (1981) show that managers are engaged in conglomerate (or diversified) mergers to decrease their risk of losing job and professional reputation.

By examining a sample of acquisitions between 1981-1992, Servaes and Zenner (1996) document that announcement returns are lower for firms that use the advice of investment banks. In a recent study, however, Golubov et al. (2012) show that the negative impact of investment advisors is not a pervasive feature in the market. They provide evidence that financial advisors deliver higher bidder returns in public acquisitions.

In addition to the above-mentioned factors, many researchers try to explain the M&A returns using the fundamental characteristics of bidder and targets. Size effect of acquirer is a well-known phenomenon in the literature. Moeller et al. (2004) show that shareholders of small (large) acquiring-firms profit (loss) when acquisitions are announced, and this is robust to

[26] A strand of M&A literature study the cross-border deals, i.e., the deals in which the acquirer and target are from two different countries. M&A return determinants which are introduced in this domain are typically country-specific factors which are not the focus of this study.

firm and deal characteristics. In a related paper, Alexandridis et al. (2013) study the size effect of targets. They show that the value of acquirers in deals characterized by large targets destroy considerably more than in small ones.

Using a sample of successful tender offers, Lang et al. (1991) document that acquirer returns are negatively changes with cash flow for firms with low Tobin's Q. Maloney et al. (1993) provide evidence regarding the significant impact of leverage on M&A outcome for acquiring firms. Harford (1999) shows that acquisitions by cash-rich firms are value destroying activities. In a recent paper, Gao (2011) confirms that announcement returns are lower for a bidder with a higher excess cash reserve.

3.2.1.2 Industry-level factors

Some argue that industry-level shocks should be viewed as the top driver of M&A activity (e.g., Weston et al., 2004). Their argument is that aggregate merger waves are caused by the clustering of industry-level waves (e.g., Harford, 2005; Mitchell and Mulherin, 1996; Ovtchinnikov, 2013).

One of the widely studied industry-level shocks is deregulation. Ovtchinnikov (2013) document that cash and bankruptcy mergers (mergers where either the bidder or the target has the Altman's Z-score below 2.7) in deregulated industries is significantly higher following industry deregulation. In addition, he finds that. Deregulated industries in this study are airlines, natural gas, oil, railroads, telecommunications, trucking, and utilities. Relying on their empirical results, Mitchell and Mulherin (1996) confirm that a large fraction of M&A activities during the 1980s was driven by macro shocks including deregulation. In this study, we follow Ovtchinnikov (2013) and Harford (2005) to identify year-industries which experience major federal deregulations.

In addition to industry shocks, some other industry-related characteristics are examined in the literature as potential determinants of M&As. For example, Guidi et al. (2020) investigate the effect of takeover socially undesirable targets (i.e., 'sin stocks') on shareholder's wealth of acquirers. Based on Fama-French 48 industry classification code, they define sin stocks which belong to alcohol, tobacco, and guns/defence groups. They show that market negatively reacts to sin acquisitions in comparison to conventional deals.

Initial industry bidder is another industry-related factor which has been specially considered in literature (e.g., Cai et al., 2011; Song and Walkling, 2000, 2011; Wang and Yin, 2018). For instance, Cai et al., (2011) show that the performance of subsequent bidders in the industry are under the influence of the first transaction of that industry. Particularly, they document that subsequent bidders have positive abnormal returns around the time of initial industry bid announcements.

3.2.1.3 Macro-level factors

A new strand of literature attempt to examine the effect of different types of macro-level uncertainties on different aspects of M&As. Bonaime et al. (2018) examine the effect of political uncertainty on M&A activity of US firms over 1985 to 2014. Using policy uncertainty index of Baker et al. (2016), they provide evidence that political uncertainty negatively affects merger and acquisition activities in number and value as well as the likelihood of commencing a new wave on M&As in the next year. In a similar paper using the same index of Baker et al., Nguyen and Phan (2017) find that policy uncertainty decreases (increases) the M&A activities (time to complete M&A deals).

Hao et al. (2022) investigate the relationship between geopolitical risk and M&A activity. To measure the geopolitical risk, they utilize a new metric developed by Caldara and Iacoviello (2022). Their findings show that geopolitical risk negatively affect the merger activity both inside and outside (cross-border deals) the US, supporting the real option channel.

Other macro drivers like merger waves, market valuation, etc., are also considered in the literature to describe the M&As activity. For example, Bouwman et al. (2009) compare the characteristics of booming-market bidders with those of depressed-market bidder. They show that acquirers who operate in times of high-valuation markets, identified by the detrended PE ratio, have significantly higher announcement returns than those operate in times of low-valuation markets. But this finding is reversed in the long run. They attribute the long-run underperformance of these acquirers to the herding behaviour of managers. Overall, they conclude that merger performance is correlated with the state of the market.

3.2.2 Application of machine learning in M&A

Liu et al. (2022) examine the effect of uniqueness of the bidder-target relationship on the merger synergies creation. Noting that measuring the uniqueness of bidder-target relations is empirically challenging, they define a new measure for this purpose based on the conditional dependence (i.e., off-diagonal elements of the precision matrix) between stock returns of bidder and target. They utilize the graphical LASSO technique of Friedman et al. (2008) to create a sparse precision matrix. Because there are thousands of stocks in the market, the precision matrix, which is the inverse return of covariance matrix, is very high dimensional and the standard OLS method is not feasible for such a high-dimensional estimation problem. Using this novel ML-based measure of uniqueness, Liu et al. (2022) document that unique relatedness is associated with a significant increase in merger synergies.

Wiedemann and Niederreiter (2021) use classifier LASSO method, developed by Su et al. (2016), to determine the important institutional and economic drivers behind cross-border M&A completion ratios between 2004 and 2018. Their findings show that pre-clustering of countries into developed and emerging economies, which is usually used in the M&A context, is not informative for explaining deal completion. They document that in a cluster with more (fewer) EU member states, more effective governments, and higher-quality regulations negatively (positively) impact the completion likelihood.

Utilizing ensemble learning method, Yang et al. (2014) try to develop a prediction model for M&A activity in six technology industries including electronics, communications, computer equipment, machinery, prepackaged software, and chemical. In addition to financial and managerial variables, they consider a large set of technological indicators derived from patent documents as potential predictors in their prediction model. Evaluation results based on M&A data from Taiwanese and Japanese companies over 1997-2008 show that incorporation of the technological indicators of both bidder and targets significantly improves the predictive power of the model.

3.3 Data and sample

3.3.1 Data sources

We start collecting data on M&A from Thomson Financial’s Securities Data Company (SDC) database. We consider all acquisitions made by public US bidders over the period 1986 to 2019, containing all types of targe firms, i.e., public, private, or subsidiary. We follow the common practice in literature to narrow the sample (e.g., Bonaime et al., 2018; Croci and Petmezas, 2015; Hao et al., 2022; Moeller et al., 2007): 1) deal transaction value must be above US$ 1 million, 2) acquirer’s market value must be greater than US$ 1 million, 3) target-to-acquirer relative size must be greater than 1%, 4) the acquirer held less than 10% of target’s shares prior to acquisitions and ended up having more than 50% of the target's equity (i.e., control acquisition). Firms with SIC code 6000-6999 (financials) and 4900-4999 (utilities) are excluded from the sample, following Cai et al. (2011) and Hao et al. (2022).

Then, we supplement this data with CRSP (for bidder run-up, cumulative abnormal return, etc.), Compustat (for accounting factors like operating cash flow, dividend, capital expenditure, R&D expense, etc.), I/B/E/S (for standard deviation of the long-term earnings growth forecasts and number of analysts), Thomson/Refinitiv (for insider ownership), and FRED (for interest rate spread). Our final sample consists of 15,285 observations from 5,040 unique bidders covering 1986-2019. It also contains data from 15,199 unique target firms.

3.3.2 Variable definition

3.3.2.1 Dependent variable

Our dependent variable is the cumulative abnormal return (CAR) around the announcement date. In fact, CAR is the standard proxy in event studies (e.g., Brown and Warner, 1985) and it is widely used to measure the merger performance in M&A literature (e.g., Bonaime et al., 2018; Croci and Petmezas, 2015; Fuller et al., 2002).

Abnormal returns are estimated by the following market model (e.g., Fuller et al., 2002):

$$AR_{it} = R_{it} - r_m \tag{3.1}$$

where R_{it}, and r_m are the return for firm i at day t, and the value-weighted market return, respectively. The difference between R_{it}, and r_m is named *abnormal returns* (i.e., AR_{it}). Since the impact of an event on firm value may not be fully revealed on a single day, event studies often examine the returns for a usually symmetric period around an event. It is called the *event window* (e.g., Aybar and Ficici, 2009). The sum of abnormal returns over an event window is the so-called *cumulative abnormal return* (or CAR). That is:

$$CAR(-T,T) = \sum_{t=-T}^{T} AR_{it} \tag{3.2}$$

where $T \in \{1,2,3,\dots\}$ determines the length of the event window. $T = 0$ is the announcement date in for a given deal.

Many studies can be found in M&A literature that use CARs within a short length window around the deal date, say 3 days which is denoted by $CAR(-1,1)$, in evaluating M&A announcement period return (e.g., Alexandridis et al., 2012; Allen et al., 2004; Bonaime et al., 2018; Moeller et al., 2007). Thus, our primary measure for M&A deal performance is the 3-day cumulative abnormal returns, i.e., $CAR(-1,1)$, around the announcement date. Allen et al. (2004) designate the 3-day window as the 'standard' duration for calculating CARs. However, Gao (2011) warns about the one-day inaccuracy of the announcement date by SDC. In fact, for a random sample of 500 acquisitions, Fuller et al. (2002) find that the announcement dates provided by SDC are correct for 92.6% of the sample. Therefore, for robustness check, we use the 8-day cumulative abnormal returns, i.e., $CAR(-4, 4)$, as alternative dependent variable. A wider window captures most, if not all, of the announcement effect, without introducing substantial noise into our analysis (Masulis et al., 2007).

3.3.2.2 Independent variables

In our empirical analysis, we consider a comprehensive set of forty-nine potential variables affecting CARs, identified from the previous studies (e.g., Bradley et al., 1988; Croci and Petmezas, 2015; Karampatsas et al., 2014; Lang et al., 1991; Moeller et al., 2004; Ovtchinnikov, 2013; Travlos, 1987; Wang and Yin, 2018).

These variables cover a diverse range of groups of M&A determinants including bidder, target, and deal characteristics (e.g., bidder size, relative size, type of acquisition, method of payment, etc.), industry and macro-level determinants (e.g., industry deregulation, initial industry bidder, policy uncertainty, etc.). The definition of these variables is provided in Appendix 3.2. Following Croci and Petmezas (2015), we winsorize all non-binary variables at 1% on both tails.

3.4 Methodology: Double machine learning

The double (or debiased) machine learning (DML) is a causal machine learning algorithm which combines the predictive power of traditional machine learning methods (e.g., LASSO, random forest, etc.) with the identification concept from the econometrics literature for estimating causal effects.

The DML procedure, developed by Chernozhukov et al. (2017, 2018), produces an unbiased and approximately normally distributed estimator. It is also a root-N consistent estimation method, where N is the sample size, for the parameter of interest. Quintas-Martinez (2022) study the finite sample performance of DML method. Owing to the widespread adoption of DML, numerous extensions of this methodology have been put forth within the academic literature (e.g., Agboola and Yu, 2023; Chang, 2020; Chiang et al., 2022; Liu et al., 2021).

To introduce the DML procedure, consider the following partially linear regression models:

$$Y_{it} = \theta_0 D_{it} + g(X_{it}) + U_{it} \tag{3.3}$$

$$D_{it} = m(X_{it}) + V_{it} \tag{3.4}$$

where Y_{it} is the dependent variable for firm i at deal date t, which would be one of the two proxies for merger performance, i.e., $CAR(-1, 1)$ and $CAR(-4, 4)$. D_{it} is the variable of interest (i.e., target variables) that we want to estimate its effect, i.e., θ_0, on M&A returns. X_{it} is a vector containing variables (i.e., cofounders) which may affect the relationship between dependent variable and target variables. U_{it} and V_{it} are error terms. $g(.)$ and $m(.)$ are two nuisance functions which connect, not necessarily linearly, cofounders to dependent and target variables, respectively.

The naïve approach in estimating θ_0 is, first, approximating the nuisance function g with a machine learning method in a regression of Y against $g(X)$, then, estimating θ_0 by implementing the traditional OLS method on Equation (3.3).[27] Simulation analyses of Chernozhukov et al. (2018) show that the naïve estimator suffers from the so-called regularization bias. To remove the biasedness of the naïve estimator, they propose to 'partial out' the effect of confounders from D using Equation (3.4). This step produces the orthogonalized residuals (i.e., $D_{it} - \widehat{m}(X_{it})$) which are used in constructing the DML estimator as follows:

$$\hat{\theta}_0 = \left(\frac{1}{n}\sum_i \sum_t (D_{it} - \widehat{m}(X_{it}))D_{it}\right)^{-1} \frac{1}{n}\sum_i \sum_t (D_{it} - \widehat{m}(X_{it}))(Y_{it} - \hat{g}(X_{it})) \tag{3.5}$$

where $\widehat{m}$ and $\hat{g}$ are approximations for two nuisance functions generated by traditional machine learning methods.[28]

In addition to the orthogonalization technique, cross-fitting is another ingredient of DML procedure which is used to improve the predictive ability of machine learning methods in predicting orthogonalized regressors (Chernozhukov et al., 2018). In fact, cross-fitting is a data-splitting technique in which estimating $\widehat{m}$ and $\hat{g}$ is done using training set while $D_{it} - \widehat{m}(X_{it})$ and $Y_{it} - \hat{g}(X_{it})$ are obtained by test set. Two-fold (i.e., splitting the sample into two equally sized groups randomly) cross-fitting is the simplest case of this technique. In this case, each split plays the role of training set and test set once. According to the recommendation of Chernozhukov et al. (2018, p. 24), we utilize four-fold cross-fitting as a

[27] By substituting the nuisance function g with its approximate function, say $\hat{g}$, the only parameter in Equation (2.1) would be θ_0. Thus, the OLS method easily can be conducted to estimate the parameter of interest in a regression of $y - \hat{g}$ against D.

[28] The name of DML method, i.e., double machine learning, comes from the dual use of machine learning methods in estimating nuisance functions g and m.

moderate value for the number of splits which works better than the smallest ones in simulations analysis.

We use DoubleML package (Bach et al., 2021) in R to implement the DML technique. Following Yang et al. (2020), two nuisance functions g and m are learned by gradient boosting method (GBM).[29] Yang et al. (2020) show with simulations analysis that the DML in combination with GBM produces 'fairly robust' results relative to other machine learning techniques. To check the sensitivity of our results with respect to the machine learner, we substitute GBM with LASSO and regression trees in further analysis section. Hyperparameters of nuisance functions learners, i.e., shrinkage parameter in LASSO, complexity parameter in regression trees and number of trees in GBM, are selected by 10-fold cross-validations (CV), following Yang et al. (2020). Coping with cross-sectional dependence among deals derived from same bidders, we use cluster robust version of DML recently developed be Chiang et al. (2022).[30] Finally, following Hansen and Siggaard (2023) we utilize standardized variables in empirical analysis for comparability purpose.

3.5 Results

3.5.1 Descriptive statistics

In this study, we examine the information content of selected variables for the short-run abnormal returns around takeover announcement date. Summary statistics of these variables appear in Table 3.1.

Private deals account for the major share of the overall takeover activity in our sample (85%). Cash payment (a combination of cash and stock) is used in 40% (42%) of acquisition bids. Diversifying acquisitions represent 59% of the sample. These summary statistics are comparable with those of prior studies (e.g., Cortes and Marcet, 2023; Croci and Petmezas, 2015).

The value of acquisition deals is approximately US$ 391 million, on average, with a standard deviation of US$ 1084 million. This high degree of variability is sensible as we observe very low and high values of transaction in our sample: from US$ 2 million to US$ 7,940 million. In fact, very large and small transaction values, on average, have been reported in the literature (e.g., Croci and Petmezas, 2015; Golubov et al., 2012).

[29] Gradient boosting method is briefly introduced in Appendix 2.2.
[30] For example, about five percent of bidders in our sample are involved in at least ten takeovers.

The inside ownership in our sample is about 12%, on average, which is consistent with Ambrose and Megginson (1992). The extent of information asymmetry about targets is greater than that of acquirers: 5.39 average analysts who follow acquirers versus 0.45 average analysts for targets. Finally, summary statistics for accounting predictors, e.g., cash ratio, free cash flow, operating cash flow, leverage, capital expenditure, tangible assets, etc., are consistent with prior studies which use these variables (e.g., Hao et al., 2022; Kaplan and Weisbach, 1992; Wang and Yin, 2018).

Table 3.1 Summary statistics

	# of obs.	Mean	Median	Min.	Max.	Std.
Target status	15,285	0.15	0.00	0.00	1.00	0.35
Method of payment	11,604	0.40	0.00	0.00	1.00	0.49
Bidder size	15,285	4183.09	741.53	12.87	91852.08	1.82
Bidder market-to-book value	14,644	3.64	2.46	-7.56	33.20	4.78
Relative size of target and acquirer	15,285	0.22	0.08	0.01	2.45	0.38
Diversifying	15,285	0.59	1.00	0.00	1.00	0.49
Tender-offer	15,285	0.04	0.00	0.00	1.00	0.18
Serial acquirers	15,285	0.12	0.00	0.00	1.00	0.32
Bidder PE	14,632	20.38	16.67	-313.89	557.85	86.95
Sigma	15,282	0.03	0.03	0.01	0.10	0.02
Bidder number of analysts	15,285	5.39	3.00	0.00	30.00	6.43
Bidder run-up	15,285	-0.27	-0.08	-4.24	0.24	0.64
Bidder age	15,285	14.79	9.00	1.00	79.00	15.64
Competing	15,285	0.08	0.00	0.00	1.00	0.27
Deal attitude	15,285	0.00	0.00	0.00	1.00	0.05
Transaction value	15,285	390.95	63.78	1.76	7939.99	1083.73
Mixed offer	11,604	0.42	0.00	0.00	1.00	0.49
Bidder Tobin's Q	14,644	2.35	1.73	0.72	13.86	1.99
Cash	15,156	0.20	0.11	0.00	0.88	0.22
Free cash flow	12,302	0.07	0.11	-1.31	0.43	0.23
Operating cash flow	11,222	0.25	0.22	-0.36	1.04	0.22
Leverage	15,149	0.23	0.19	0.00	0.93	1.72
Capital expenditure	14,975	0.05	0.03	0.00	0.39	0.07
Tangible assets	14,683	0.23	0.14	0.00	0.90	0.23
Sales growth	14,693	0.51	0.17	-0.52	11.12	1.42
R&D expense	13,625	0.07	0.03	0.00	0.45	0.08
Inside ownership	13,834	0.12	0.03	0.00	0.85	0.19
Bidder illiquidity	15,280	0.00	0.00	0.00	0.01	0.00
Bidder efficiency	13,579	0.34	0.29	0.07	1.00	0.17
Bidder managerial ability	13,579	0.01	-0.02	-0.22	0.50	0.13
Bidder efficiency ranking	13,579	0.65	0.70	0.10	1.00	0.26
Bidder managerial ability ranking	13,579	0.56	0.60	0.10	1.00	0.29
Acquirer’s rating existence	11,493	0.37	0.00	0.00	1.00	0.48
Herfindahl index	15,238	0.06	0.04	0.01	0.32	0.05
High-tech deal	15,285	0.35	0.00	0.00	1.00	0.48
Initial industry bidder	15,285	0.20	0.00	0.00	1.00	0.40
Sin industry dummy	15,212	0.00	0.00	0.00	1.00	0.03
Merger waves	15,285	0.58	1.00	0.00	1.00	0.49
Market valuations	15,285	0.08	0.15	-2.93	2.65	0.96
M&A liquidity	15,238	0.03	0.02	0.00	0.17	0.03
Policy uncertainty	15,285	107.13	96.55	67.14	188.70	30.92
Geopolitical risk	15,285	4.49	4.45	3.93	5.17	0.32
Interest rate spread	14,698	2.23	2.11	1.56	3.49	0.49
Target advisors	15,285	0.42	0.00	0.00	1.00	0.49
Bidder advisors	15,285	0.34	0.00	0.00	1.00	0.47
Regulation-deregulation	15,285	0.03	0.00	0.00	1.00	0.16

Earnings growth forecasts	8,919	5.21	3.63	0.00	30.45	5.12
Target's number of analysts	15,285	0.45	0.00	0.00	13.00	1.87
Dividend	15,136	0.33	0.00	0.00	1.00	0.47

Note: This table presents the summary statistics of M&A return determinants. Variable definitions are provided in Appendix 3.2.

3.5.2 Chronological order analysis

As the starting point, we follow Feng et al. (2020) and estimate the effect of M&A return determinants using DML technique chronologically. To do so, we consider factors introduced before 1990 as benchmark. We then recursively add subsequent factors to benchmark in assessing the effect of a new factor. The benchmark factors include tender-offer (Dodd and Ruback, 1977), diversifying (Amihud and Lev, 1981), relative size of target and acquirer (Asquith et al., 1983), bidder size and bidder market-to-book value (Palepu, 1986), mixed offer (Travlos, 1987), method of payment (Travlos, 1987), competing (Bradley et al., 1988), and bidder's Q (Lang et al., 1989).

Table 3.2 introduces the factors produced in the literature onward 1990. Factors with significant effects at the 1% level on M&A returns, proxied by $CAR(-1, 1)$, are bolded. In the years with more than one factor, we adjust *p*-values using Hochberg's (1988) correction method to avoid false discoveries. When implementing the DML method, we incorporate industry and year fixed effects to account for potential industry-specific and year-specific unobservables, following Hansen and Siggaard (2023). Industry dummies are generated using the acquirer's four-digit SIC codes. Furthermore, year dummies are constructed based on the acquirer's fiscal year.

The results show that from among the large number of factors introduced in the literature, only a select few exhibit explanatory power for short-term M&A returns. Particularly, we find evidence to support the significant effects of target and bidder advisors (Servaes and Zenner, 1996), target status (Chang, 1998), and target's number of analysts (Chemmanur et al., 2009). Appendix 3.3 presents the DML estimation results of M&A return determinants recursively by year of publication.

Table 3.2 Significant determinants of M&A returns in chronological order analysis

Year	# of controls	New factors
1991	9	Free Cash Flow, Cash, Deal Attitude
1992	12	Inside ownership, Operating cash flow
1993	14	Leverage
1996	15	**Target Advisors**, **Bidder Advisors**, Bidder Run-up, Merger waves, Regulation-Deregulation
1998	20	**Target status**
1999	21	Dividend, Sales Growth

2000	23	Herfindahl Index
2001	24	High-tech deal
2002	25	Serial Acquirers
2003	26	Bidder PE
2005	27	Interest Rate Spread, Tangible Assets, R&D expense
2007	30	Sigma, long-term earnings growth forecasts (LTG)
2009	32	Acquirer's Number of Analysts, **Target's Number of Analysts**, Market valuations
2011	35	Initial industry bidder, M&A Liquidity
2012	37	Bidder age
2013	38	Acquirer's Illiquidity
2014	39	Acquirer's Rating Existence
2017	40	Acquirer's Efficiency, Acquirer's Efficiency ranking, Policy uncertainty
2018	43	capital expenditure
2020	44	Sin Industry dummy, Acquirer's managerial ability, Acquirer's managerial ability ranking
2022	47	GPR (Geopolitical Risk)

Note: Tis table introduces the factors produced in the literature onward 1990. Factors with significant effects at the 1% level are bolded. The dependent variable is CAR(-1,1). In the years with more than one factor, we adjust *p*-values using Hochberg's (1988) correction method to avoid false discoveries. Industry and year fixed effects are included.

3.5.3 Thematic grouping

To investigate the impact of M&A return determinants, we adopt the 'forward stepwise procedure' as outlined by Feng et al. (2020). We start with a small set of 'preselected' determinants as benchmarks. We then run the DML method on the first groups of determinants. We iterate this procedure recursively, so that the set of 'preselected' factors expands by the determinants in the next group at each iteration.

Unlike Feng et al. (2020), we consider a group of variables at each iterative step, as opposed to the exclusive focus on a single variable. Categorizing variables in separate groups and estimating their effect simultaneously allows us to consider the hidden inter-relationships between various factors within specific groups, thereby gaining a comprehensive understanding of their effects on M&A returns. Exploiting the cluster structure of explanatory variables in predicting returns has attracted considerable attention in recent years (e.g., Freyberger et al., 2020; Huang and Shi, 2023). However, there is a concern on data snooping bias caused by multiple hypothesis testing. To address this issue, we adjust *p*-values using Hochberg's (1988) correction method in each iteration.

Based on a *prior* knowledge of researcher and due to the lack of well-accepted benchmarks in existing M&A literature, we consider seven commonly used predictors as benchmarks including relative size, target status, tender-offer, diversifying, bidder market-to-book value, method of payment, and bidder size. Considering these variables as benchmarks are supported by evidence provided by King et al. (2004; 2021). By surveying a large number of studies (94 papers) from different disciplines, King et al. (2004) introduce the following four variables as ‘commonly’ used predictors to explain the acquisition performance: diversifying, method of payment, acquisition experience, and conglomerate firms. By expanding the number of research for the meta-analysis (220 papers), King et al. (2021) augment the identified important variables with twelve more others which include relative size, market-to-book ratio, and bidder size.

Moreover, we thematically categorize M&A return determinants in nine groups including bidder characteristics, deal-specific variables, accounting variables, other bidder characteristics, industry characteristics, market characteristics (related to M&As), other market characteristics (other macros), advisors, other variables. We follow a conservative approach in the designing of variable groups and their sequential incorporation into the model. This methodology is structured to minimize the loss of observations at each stage while maximizing the utilization of the available dataset. Table 1 presents a brief description of M&A return determinants grouping that we use in the main analysis.

Although we follow a common sense in thematic grouping of variables, we conduct some confirmatory factor analysis (CFA) to support our grouping nature. First, we check for Tucker-Lewis index (TLI) and comparative fit index (CFI). As a rule of thumb, values greater than 0.9 for these indexes indicate good fit of the factor model in each group (e.g., Hu and Bentler, 1999). In fact, for two groups, i.e., deal-specific variables, and other targets, these indexes are greater than 0.9. For many other groups these indexes are very close to this cutoff point. Second, we also compute the root mean squared error of approximation (RMSEA). Values between 0.05 and 0.08 indicate reasonable approximate fit of the model (e.g., Hu and Bentler, 1999). Again, the best statistics are obtained for deal-specific variables, and other targets with 0.026 and 0.029, respectively. Third, factor loadings on observable characteristics are statistically significant at the 10% level using *z*-statistics in the vast majority of cases, indicating high correlation between variables and the corresponding latent factors. We report the factor loadings of different variables on the corresponding laten variable in Appendix 3.4.

In addition to the CFA analysis discussed above, including two variables of diversifying and method of payment among the benchmarks is consistent with the meta-analysis results of King et al. (2004). By surveying studies in management, they introduce the following four variables as ‘commonly’ used predictors to explain the acquisition performance: diversifying, method of payment, acquisition experience, and conglomerate firms.

We employ DML method in the framework of thematic grouping for $CAR(-1,1)$, and $CAR(-4,4)$, separately. Table 3.3 presents a summary of DML analysis in this context. In general, only five variables are identified as important predictors for $CAR(-1,1)$. In contrast, the number of variables with significant effects at least at the 10% level is eight for $CAR(-4,4)$.

Table 3.3 Description of DML analysis based on thematic grouping

					# of significant effects	
id	Group name	# of obs.	# of controls	# of targets	$CAR(-1,1)$	$CAR(-4,4)$
1	Bidder characteristics	11,113	7	6	0	0
2	Deal-specific variables	11,113	13	4	1	1
3	Accounting variables	7,351	17	9	0	1
4	Other bidder characteristics	5,412	26	7	0	1
5	Industry characteristics	5,379	33	4	1	1
6	Market characteristics (*Related to M&As*)	5,379	37	3	0	1
7	Other market characteristics (*Other macros*)	5,339	40	3	0	1
8	Advisors	5,339	43	2	2	1
9	Other variables	3,549	45	4	1	1

Note: This table describes the results of DML analysis for $CAR(-1,1)$, and $CAR(-4,4)$ using thematic grouping approach.

Table 3.4 presents the DML analysis results for $CAR(-1,1)$. Since in each group the effects of variables are estimated simultaneously, we adjust *p*-values using Hochberg's (1988) correction method for valid simultaneous inference, following Hansen and Siggaard (2023).[31] Heteroskedasticity-robust clustered standard errors at firm level are utilized to calculate *t*-statistics based on Chiang et al.'s (2022) methodology.

The results show that a sparse set of variables can be considered as relevant predictors for merger performance, beyond the benchmarks. For example, in the first group of bidder characteristics, none of the effects are statistically significant. And in the second group of deal-specific variables, we find only one significant effect for transaction value with effect size -0.099. This is a challenging finding that contradicts the common wisdom in the literature regarding the pre-assumed importance for many of these variables. We will discuss the significant and non-significant effects in detail in the following sections.

[31] In an un-reported analysis, we also utilized Bonferroni's correction for adjusting *p*-values. The obtained results largely support our findings based on Hochberg's (1988) correction method.

Table 3.4 DML results based on thematic grouping: CAR(-1,1)

Group name	Targets	# of obs.	DML w. GBM	Adj. *p*-value
Bidder characteristics	Serial acquirers	11,113	-0.013	1.000
	Bidder PE	11,113	-0.004	1.000
	Sigma	11,113	0.009	1.000
	Bidder number of analysts	11,113	-0.026	0.129
	Bidder run-up	11,113	-0.029	0.453
	Bidder age	11,113	0.017	0.418
Deal-specific variables	Competing	11,113	0.008	0.544
	Deal attitude	11,113	-0.004	0.544
	Transaction value	11,113	-0.099	0.000
	Mixed offer	11,113	0.020	0.544
Accounting variables	Bidder Tobin's Q	7,351	-0.002	0.180
	Cash	7,351	-0.007	0.825
	Free cash flow	7,351	-0.008	0.825
	Operating cash flow	7,351	-0.010	0.554
	Leverage	7,351	0.000	0.825
	Capital expenditure	7,351	-0.025	0.676
	Tangible assets	7,351	-0.001	0.825
	Sales growth	7,351	-0.001	0.825
	R&D expense	7,351	-0.043	0.136
Other bidder characteristics	Inside ownership	5,412	0.003	0.856
	Bidder illiquidity	5,412	-0.034	0.856
	Bidder efficiency	5,412	-0.039	0.435
	Bidder managerial ability	5,412	-0.020	0.856
	Bidder efficiency ranking	5,412	-0.032	0.522
	Bidder managerial ability ranking	5,412	-0.009	0.856
	Acquirer’s rating existence	5,412	-0.031	0.522
Industry characteristics	Herfindahl index	5,379	0.018	0.428
	High-tech deal	5,379	-0.051	0.045
	Initial industry bidder	5,379	0.015	0.425
	Sin industry dummy	5,379	-0.009	0.428
Market characteristics (*Related to M&As*)	Merger waves	5,379	0.010	0.886
	Market valuations	5,379	0.022	0.461
	M&A liquidity	5,379	0.002	0.886
Other market characteristics (*Other macros*)	Policy uncertainty	5,339	0.010	0.618
	Geopolitical risk	5,339	0.020	0.463
	Interest rate spread	5,339	0.034	0.146
Advisors	Target advisors	5,339	-0.037	0.027

	Bidder advisors	5,339	-0.046	0.018
Other variables	Regulation-deregulation	3,549	0.015	0.415
	Earnings growth forecasts	3,549	0.018	0.415
	Target's number of analysts	3,549	-0.071	0.036
	Dividend	3,549	-0.024	0.415

Note: This table reports the estimated effects of targets on 3-day cumulative abnormal return, $CAR(-1,1)$, using double machine learning method (DML) with four-fold cross-fittings. Nuisance functions are learned by gradient boosting method (GBM). P-values are adjusted using Hochberg (1988) correction for valid simultaneous inference. Heteroskedasticity-robust clustered standard errors at firm level are utilized to calculate t-statistics based on Chiang et al. (2022). The controls for the first group are relative size, target status, tender-offer, diversifying, bidder market-to-book value, method of payment, and bidder size. The controls for the second group are the union of the controls and the targets in the first group, and so on. Variable definitions are provided in Appendix 3.2.

Table 3.5 presents the results of DML analysis for $CAR(-4,4)$. Similar to the results for $CAR(-1,1)$, a small set of variables exhibit a significant effect on merger performance. The number of significant effects, however, is slightly greater than that of $CAR(-1,1)$: 8 *vs.* 5. It seems that lengthening the event window from three days in $CAR(-1,1)$ to nine days in $CAR(-4,4)$ amplifies the information content of some of the variables which do not have significant contribution in very short time horizon around the announcement date. This finding suggests that it takes time the role of some characteristics to be revealed in the market in predicting abnormal return. Perhaps this is the reason that we observe the significance of some of the market characteristics, i.e., market valuations and geopolitical risk, in predicting $CAR(-4,4)$, while these variables are not of importance in predicting $CAR(-1,1)$. For a comprehensive discussion on the importance of time horizon in even studies, including M&As, see Jeng (2015).

Table 3.5 DML results based on thematic grouping: CAR(-4,4)

Group name	Targets	# of obs.	DML w. GBM	Adj. *p*-value
Bidder characteristics	Serial acquirers	11,113	0.000	0.966
	Bidder PE	11,113	0.005	0.966
	Sigma	11,113	0.028	0.571
	Bidder Number of Analysts	11,113	-0.12	0.741
	Bidder run-up	11,113	0.025	0.670
	Bidder age	11,113	0.017	0.441
Deal-specific variables	Competing	11,113	-0.005	0.673
	Deal attitude	11,113	-0.006	0.673
	Transaction value	11,113	-0.067	0.000
	Mixed offer	11,113	-0.007	0.673
Accounting variables	Bidder Tobin's Q	7,351	-0.005	0.072
	Cash	7,351	-0.018	0.555
	Free cash flow	7,351	0.033	0.215
	Operating cash flow	7,351	-0.008	0.589
	Leverage	7,351	0.001	0.589
	Capital expenditure	7,351	-0.017	0.589
	Tangible assets	7,351	0.006	0.589
	Sales growth	7,351	0.001	0.589
	R&D expense	7,351	-0.071	0.343

Other bidder characteristics	Inside ownership	5,412	0.010	0.867
	Bidder illiquidity	5,412	0.095	0.867
	Bidder efficiency	5,412	-0.005	0.867
	Bidder managerial ability	5,412	-0.003	0.867
	Bidder efficiency ranking	5,412	0.014	0.867
	Bidder managerial ability ranking	5,412	0.019	0.867
	Acquirer's rating existence	5,412	-0.054	0.027
Industry characteristics	Herfindahl index	5,379	0.014	0.420
	High-tech deal	5,379	-0.055	0.025
	Initial industry bidder	5,379	0.014	0.420
	Sin Industry dummy	5,379	-0.019	0.420
Market characteristics (*Related to M&As*)	Merger waves	5,379	0.006	0.743
	Market valuations	5,379	0.041	0.051
	M&A liquidity	5,379	0.005	0.743
Other market characteristics (*Other macros*)	Policy uncertainty	5,339	0.017	0.761
	Geopolitical risk	5,339	0.046	0.027
	Interest rate spread	5,339	-0.006	0.761
Advisors	Target advisors	5,339	-0.040	0.035
	Bidder advisors	5,339	-0.018	0.297
Other variables	Regulation-deregulation	3,549	0.030	0.381
	Earnings growth forecasts	3,549	-0.019	0.381
	Target's number of analysts	3,549	-0.068	0.003
	Dividend	3,549	-0.020	0.381

Note: This table reports the estimated effects of targets on 8-day cumulative abnormal return, $CAR(-4, 4)$, using double machine learning method (DML) with four-fold cross-fittings. Nuisance functions are learned by gradient boosting method (GBM). P-values are adjusted using Hochberg (1988) correction for valid simultaneous inference. Heteroskedasticity-robust clustered standard errors at firm level are utilized to calculate t-statistics based on Chiang et al. (2022). The controls for the first group are relative size, target status, tender-offer, diversifying, bidder market-to-book value, method of payment, and bidder size. The controls for the second group are the union of the controls and the targets in the first group, and so on. Variable definitions are provided in Appendix 3.2.

3.5.3.1 Significant effects

Among the significant effects for announcement returns, detected by DML, transaction value has the largest effect size in absolute value.[32] The results show that US$ 1 million increase in the value of transaction leads to a decrease of 9.9% and 6.7% in $CAR(-1, 1)$ and $CAR(-4, 4)$, respectively. The negative impact of transaction value on announcement returns is consistent with Jensen's (1986) empire-building hypothesis. According to this argument, managers tend to be involved in large takeovers to increase their power and decrease the probability of their firm becoming a takeover target, at the expense of their shareholders (Bayazitova et al., 2012). This negative effect of transaction value is also in line with the empirical findings of Bayazitova et al. (2012) and Bhagat et al. (2011).

Noticeably, both variables from the 'advisors' group, i.e., target advisors and bidder advisors, are identified as variables with significant contributions for prediction of $CAR(-1, 1)$. Even the first one, i.e., target advisors, maintains its significance for

[32] The only exception is variable targets' number of analyst under $CAR(-4, 4)$ whose effect is very close to that of transaction value: -0.068 *vs*. -0.067.

$CAR(-4, 4)$. It means that the market strongly reacts to takeovers in which the acquirer uses top tier investment banks' advice. The importance of deal advisors in determining the outcome of takeovers which we document here is in line with Servaes and Zenner (1996) and Golubov et al. (2012). This importance arises from the crucial role of information flow in M&A deals.

The negative impacts of target (i.e., -0.037 and -0.040, under $CAR(-1, 1)$ and $CAR(-4, 4)$, respectively) and bidder (i.e., -0.046 and -0.018 under $CAR(-1, 1)$ and $CAR(-4, 4)$, respectively) advisors suggest that in-house merger, in which bidding firm does not use the advisory services of an investment bank (e.g., Servaes and Zenner; 1996), gain more than other mergers. This is consistent with prior empirical findings, e.g., Rau (2000), Hunter and Jagtiani (2003), and Ismail (2010). According to Rau (2000), top-tier bankers advise their clients to offer larger premiums to targets which in turn reduces the gain of the bidder firms. However, there is still no consensus on whether hiring top-tier advisors is a value-creating or value-destroying corporate event. For example, Golubov et al.'s (2012) results support the value-creating role of investment banks with strong reputation on bidder returns, confirming the 'reputation-quality' mechanism.

High-tech deal indicator is another important factor for merger performance detected by DML. Our results indicate that high-tech deals bring statistically significantly lower merger returns for bidders. Generally, targets operate in high-tech industries, such as biotechnology, electronics, computer software, etc., are characterized by a high degree of asymmetric information, due to the nature of intangible assets embedded in those companies (e.g., Benou et al., 2007). Under this opacity, it is sensible that we find a negative impact for high-tech deal indicator. Because in such transactions, investors may have difficulty in obtaining reliable information on intangibles and hence, in evaluating the target's resources and capabilities for the acquirer (Song et al., 2021).

Directly related to the argument discussed above, i.e., information asymmetry, target's number of analysts is identified by DML as an important predictor for CARs. The obtained negative sign (-0.071 and -0.068 under $CAR(-1, 1)$ and $CAR(-4, 4)$, respectively), however, is not consistent with the intuition. Because, according to Chemmanur et al. (2009), the greater the number of analysts the lower the information asymmetry about firm value. As a result, one expects to see that acquirers of targets with more analyst coverage receive higher merger announcement returns. Nevertheless, the negative sign for the effect of target's number of analysts is consistent with the empirical findings of Cortes and Marcet (2023), and Fich et al. (2018).

A specific group of variables identified as important predictors for the $CAR(-4, 4)$, but not for $CAR(-1, 1)$, consists of macro variables. Particularly, market valuations of Bouwman et al. (2009) and geopolitical risk of Hao et al. (2022) are the two macro variables with significant effects on $CAR(-4, 4)$ with size effect 0.041 and 0.046, respectively. The positive effects on these variables are consistent with the relevant studies.

3.5.3.2 Non-significant effects

Despite the extensive use of many variables as default predictors in prior literature, DML analysis results indicate that most of them lack information content for announcement takeover returns. For example, the effect of none of the determinants from the 'bidder characteristics' and 'accounting variables' groups are statistically significant, except for bidder Tobin's Q from the accounting variables group which is statistically significant at 10% level.

Indeed, the prevalence of irrelevant predictors in the literature of merger and acquisition has already been pointed out by King et al (2004) and highlighted by Renneboog and Vansteenkiste (2019). In a survey paper utilizing meta-analytic techniques, King et al. (2004) demonstrate that the performance of acquiring firms does not vary significantly based on commonly used characteristics such as related acquisitions (or diversifying) and method of payment.

Apart from the commonly used variables, the non-significant effects on more specific variables align with findings from prior studies in most cases. For example, we find that target's coverage by analysts, and not the acquirer's coverage, has a significant effect on abnormal return. This is consistent with empirical findings of Cortes and Marcet (2023). They also find no significant effects for bidder run-up, leverage, and cash ratio. The results of Wang and Yin (2018) show that initial industry bidder, capital expenditure, and serial acquirers do not have significant effect on $CAR(-1, 1)$, and $CAR(-2, 2)$.

However, we find contradicting results for some of variables. We find no evidence to support the significant effect of sin industry dummy, for example. Guidi et al. (2020) document a significant decrease in cumulative abnormal return surrounding the announcement date for sin industry acquisition. For another example, the estimated effect for regulation-deregulation dummy variable is contrary to the findings of Ovtchinnikov (2013) in sign and significance.

3.5.4 Further analysis

3.5.4.1 Random benchmarks

In thematic grouping approach, we select the benchmarks based on a prior knowledge of researcher. There is a potential concern that selecting benchmarks based on personal views could introduce bias into the DML results. In this section, to assess the sensitivity of our results to the combination of benchmark variables, we address this issue using a completely random approach. Particularly, we examine the effect of each variable against random benchmarks.

For this purpose, we randomly select without replacement twenty controls for each variable. Then, we estimate the effect of variables using DML, one at a time. We iterate this process 100 times. At the end, we calculate the median of effects, median of absolute values of *t*-statistics, and median of *p*-values.

Table 3.6 presents the results of DML analysis using random benchmarks for $CAR(-1,1)$ in Columns (4)-(6). We also report the results of OLS in Columns (1)-(3), as a workhorse model in M&A literature, to create a benchmark for comparing the results of DML method. Columns (3) and (6) illustrates the percentage of significant effect of each variable at the 10% level over 100 repetitions. P-values of the Welch two sample *t*-test to test the differences of estimated effects between OLS and DML are reported in the last columns. The reported *t*-statistics are the median of absolute values over 100 permutations. Heteroskedasticity-robust clustered standard errors at firm level are utilized to calculate *t*-statistics based on White (1980) and Chiang et al. (2022) in OLS and DML, respectively.

Not surprisingly, five out of seven benchmark variables have statistically significant effect on $CAR(-1,1)$ based on *t*-statistics reported in Column (5). These variables are target status, method of payment, bidder size, relative size, and tender-offer. This finding supports the rationale behind considering these variables as benchmark controls in the main analysis.

Apart from the benchmarks, there is an interesting overlap between the factors that appear significant in the current analysis (where the personal view is ignored) and those were significant in the main analysis. About 60% of the significant variables found in the main analysis (i.e., high-tech deal, transaction value, and target's number of analysts) demonstrate a significance effect in the current analysis as well. This is a reasonable alignment between two different scenarios in an application of DML. In their study, Feng et al. (2020) find a

50% alignment between two different scenarios, namely the historical procedure and forward stepwise procedure, regarding their utilization of the DS method.

Although, the effects of target advisors and bidder advisors (which were significant in the main analysis) are not statistically significant, but they present a relatively high values of *t*-statistics over 100 permutations. For a better understanding of the magnitude of *t*-statistics see Figure 3.1. In fact, about 70 (30) percent of the estimated effects for the target (bidder) advisors are statistically significant in 100 permutations.

Table 3.6 DML analysis using random benchmarks: CAR(-1,1)

	OLS			DML w. GBM			
	Effect	*t*-statistics	Significant effect (%)	Effect	*t*-statistics	Significant effect (%)	Diff. (*p*-value)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Target status	-0.097	6.204***	90	-0.103	6.159***	90	0.109
Method of payment	0.052	3.350***	100	0.057	3.548***	100	0.325
Bidder size	-0.070	3.671***	70	-0.097	3.000***	90	0.000
Bidder market-to-book value	0.009	0.639	10	0.015	0.799	0	0.021
Relative size of target and acquirer	0.111	5.740***	100	0.096	4.512***	100	0.017
Diversifying	0.009	0.637	10	0.011	0.779	10	0.186
Tender-offer	0.020	1.864*	20	0.030	2.367**	30	0.519
Serial acquirers	-0.011	0.856	0	-0.010	0.800	0	0.215
Bidder PE	-0.007	0.498	0	-0.003	0.453	0	0.053
Sigma	0.011	0.702	30	-0.009	1.196	0	0.001
Bidder number of analysts	-0.032	2.257**	60	-0.031	2.152**	70	0.659
Bidder run-up	-0.022	1.023	0	-0.027	1.158	10	0.291
Bidder age	0.016	1.219	10	0.009	0.819	0	0.002
Competing	0.000	0.442	0	0.000	0.422	0	0.487
Deal attitude	0.003	0.446	0	0.003	0.500	10	0.255
Transaction value	-0.034	2.216**	70	-0.052	2.871***	80	0.000
Mixed offer	0.000	1.212	20	0.001	1.348	20	0.989
Bidder Tobin's Q	0.00	0.628	20	0.008	0.692	10	0.028
Cash	-0.029	1.563	60	-0.017	0.894	40	0.000
Free cash flow	-0.014	0.716	20	-0.017	0.815	0	0.121
Operating cash flow	-0.033	1.954*	60	-0.028	1.581	50	0.028
Leverage	-0.005	0.476	0	0.000	0.430	10	0.000
Capital expenditure	-0.030	1.977**	60	-0.025	1.651*	60	0.017
Tangible assets	0.001	0.911	10	-0.006	0.806	10	0.630

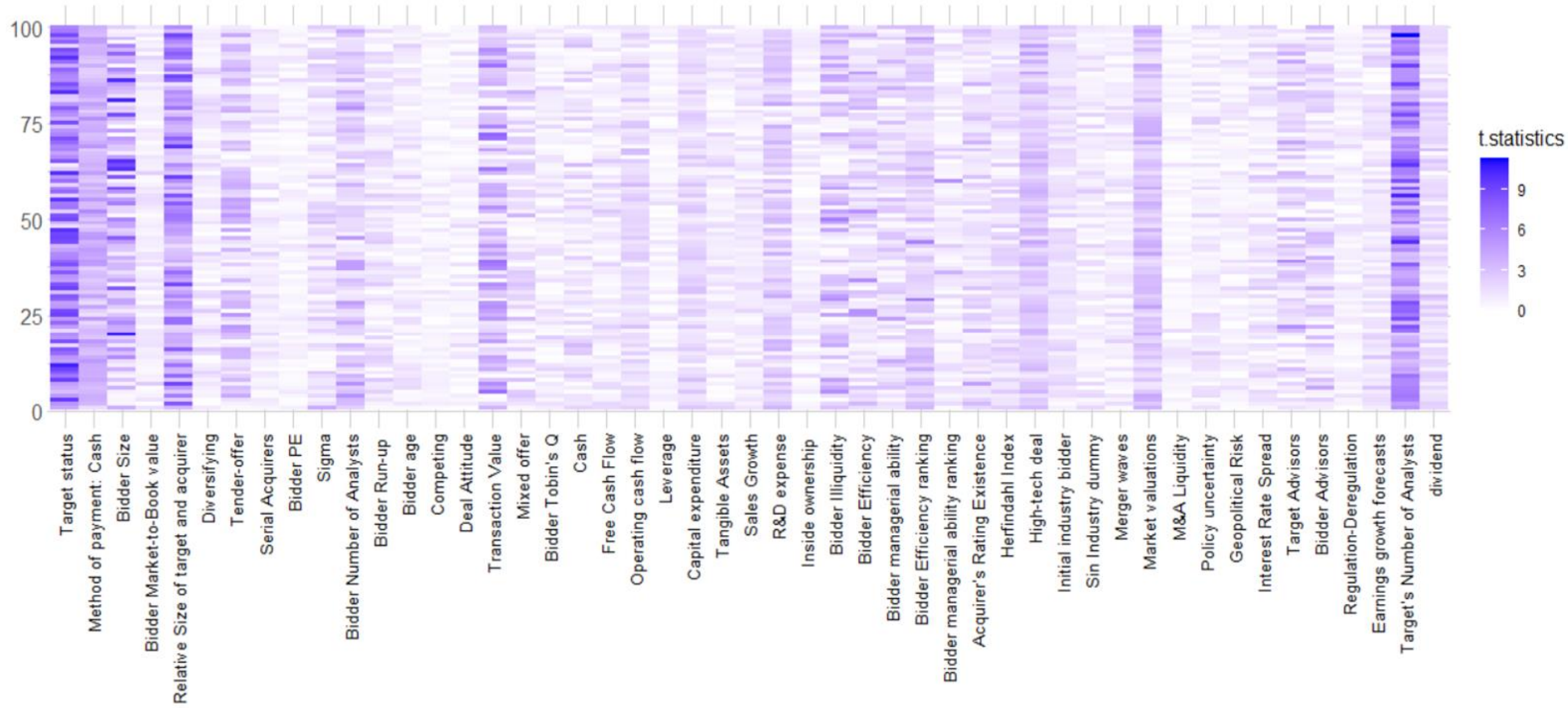
Sales growth	-0.014	0.951	10	-0.014	0.949	20	0.933
R&D expense	-0.043	2.442**	100	-0.041	2.271**	80	0.029
Inside ownership	0.013	0.896	20	0.009	0.642	0	0.031
Bidder illiquidity	0.052	2.293**	60	0.051	1.960*	50	0.314
Bidder efficiency	-0.033	1.505	50	-0.040	1.553	70	0.247
Bidder managerial ability	-0.022	1.313	20	-0.027	1.418	40	0.330
Bidder efficiency ranking	-0.040	2.083**	50	-0.053	2.095**	80	0.004
Bidder managerial ability ranking	0.006	0.982	40	0.001	0.701	40	0.026
Acquirer's rating existence	-0.014	1.004	30	-0.023	1.386	40	0.000
Herfindahl index	0.018	1.606	40	0.017	1.403	40	0.143
High-tech deal	-0.047	2.892***	90	-0.041	2.558**	80	0.295
Initial industry bidder	0.019	1.541	30	0.017	1.367	40	0.006
Sin industry dummy	-0.003	0.665	10	-0.006	0.787	30	0.219
Merger waves	-0.007	0.701	10	-0.012	0.696	10	0.012
Market valuations	0.039	2.821***	100	0.038	2.690***	90	0.270
M&A liquidity	0.003	0.361	0	0.004	0.363	0	0.136
Policy uncertainty	-0.009	0.837	20	-0.011	0.745	20	0.287
Geopolitical risk	0.009	0.633	0	0.012	0.653	10	0.006
Interest rate spread	0.013	0.853	30	0.017	0.969	30	0.066
Target advisors	-0.001	1.183	10	-0.014	1.622	70	0.001
Bidder advisors	0.011	1.437	20	-0.008	1.414	30	0.000
Regulation-deregulation	0.009	0.654	0	0.008	0.664	10	0.731
Earnings growth forecasts	0.016	0.912	10	0.021	1.177	20	0.004
Target's number of analysts	-0.083	5.105***	90	-0.089	5.330***	100	0.164
Dividend	-0.018	1.366	20	-0.022	1.626	40	0.009

Note: This table reports median values of estimated effects of target variables, one at a time, over 100 permutations of randomly selected twenty controls. The results of OLS are in Columns (1)-(3) and those of DML are reported in Columns (4)-(6). Columns (3) and (6) illustrates the percentage of significant effect of each variable at the 10% level over 100 repetitions. *P*-values of the Welch two sample *t*-test to test the differences of estimated effects between OLS and DML are reported in the last column. In DML, nuisance functions are learned by gradient boosting method (GBM). Absolute values of median *t*-statistics are reported. Heteroskedasticity-robust clustered standard errors at firm level are utilized to calculate *t*-statistics based on White (1980) and Chiang et al. (2022) in OLS and DML, respectively. Dependent variable is $CAR(-1, 1)$. Variable definitions are provided in Appendix 3.2. *, ** and *** denote significance at the 10%, 5% and 1% respectively.

In addition to above mentioned variables, some other ones, such as bidder illiquidity, capital expenditure, R&D expense, etc., also experience significant effects on $CAR(-1, 1)$. This may be because we consider each variable on its own. While in the main analysis, we estimate the effect of each group of variables simultaneously. Considering thematically related variables together, as we did in the main analysis, accounts for the potential correlation during the effect estimation process. This adjustment aids in capturing their collective impact more accurately and refining their individual effects.

It seems that the results of OLS are comparable with those of DML in terms of significant effects. Comparing Columns (1) and (4), however, shows that there exist statistically significant differences between the two methods in terms of the magnitude of the effects on about 50% of the target variables over 100 permutations, based on the reported *p*-values in the last column. The observed difference between OLS and DML is consistent with Hansen and Siggaard (2023) who try to compare the two methods using Cohen's *d* statistics. These findings suggest that DML, as a specialized method to estimate the parameter of interest in the context of high-dimensional data, should be preferred over OLS.

Figure 3.1 t-statistics derived from DML analysis using random benchmarks: CAR(-1,1)



Note: This figure illustrates the absolute values of *t*-statistics derived from DML analysis using 100 permutations of randomly selected twenty controls for each of variables. Dependent variable is $CAR(-1,1)$.

Table 3.7 presents the results of DML analysis using random benchmarks for $CAR(-4, 4)$. Similarly, Figure 3.2 illustrates the magnitude of *t*-statistics in 100 permutations. The results indicate that half of the significant effects are common between current analysis and the main one. Particularly, transaction value, high-tech deal, market valuations, and target's number of analysts, are the same in both cases.

Geopolitical risk experiences significant effects of 30% in a total of 100 repetitions, which, along with market valuations, shows the importance of macro-level variables for predicting $CAR(-4, 4)$. This is consistent with our findings in the main analysis. In addition, information related variables, i.e., target and bidder advisors, are significant in a relatively large fraction of permutations: 35% and 29%, respectively. This is in addition to the strong significance of the target's number of analysts in all replications.

3.5.4.2 Alternative machine learners

In practice, any 'sensible' machine learning methods can be used to estimate the nuisance functions in combination with DML (Chernozhukov et al., 2018). In the main analysis, we utilized GBM to estimate nuisance functions following Yang et al. (2020). In this section, we conduct the DML analysis in combination with LASSO (DML w. LASSO) and regression trees (DML w. RT) to check the robustness of our findings to the machine learner.

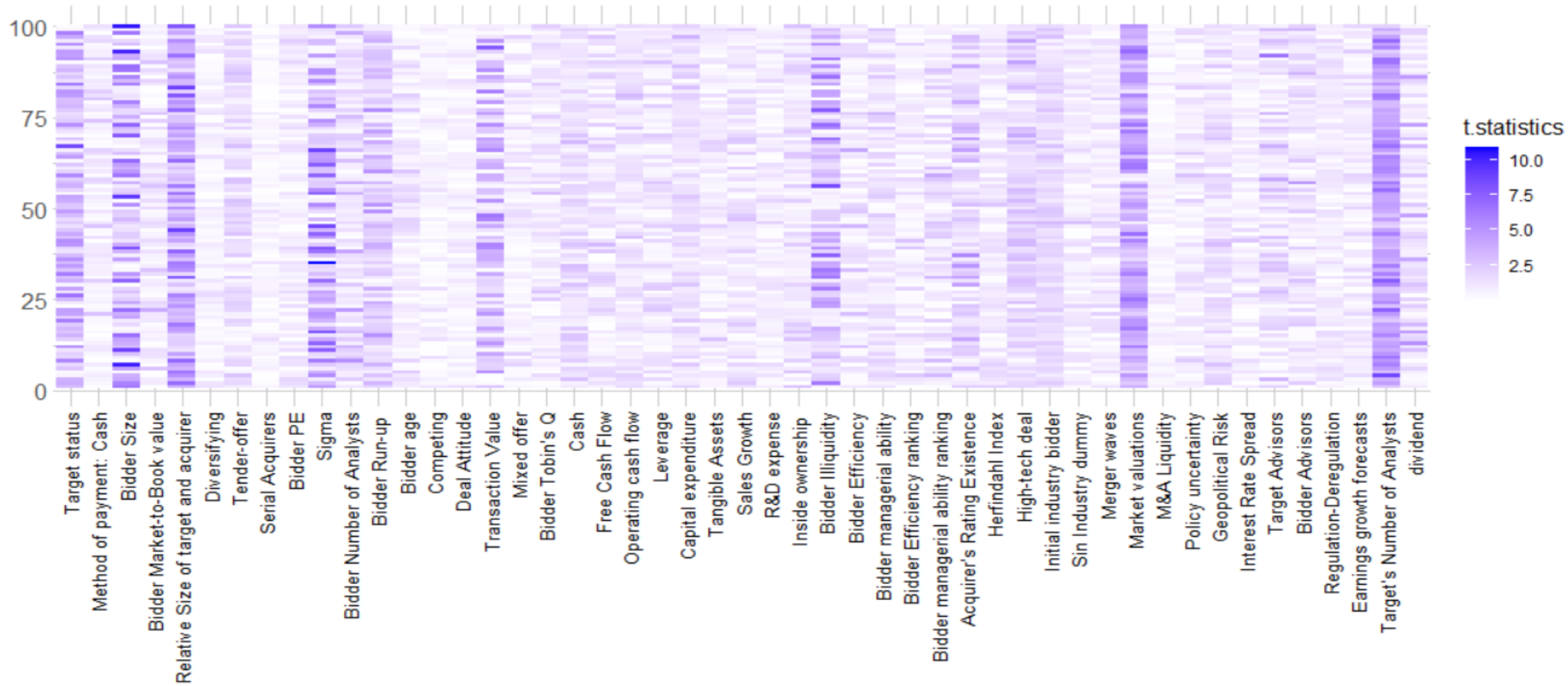
Table 3.7 DML analysis using random benchmarks: CAR(-4,4)

	OLS			DML w. GBM			Diff.
	Effect	*t*-statistics	Significant effect (%)	Effect	*t*-statistics	Significant effect (%)	(*p*-value)
Targets	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Target status	-0.037	2.652***	73	-0.044	2.754***	76	0.086
Method of payment	0.007	0.582	11	0.007	0.684	12	0.844
Bidder size	-0.082	3.494***	86	-0.090	2.792**	65	0.567
Bidder market-to-book value	0.009	0.726	17	0.010	0.859	18	0.315
Relative size of target and acquirer	0.098	5.254***	96	0.076	3.528***	92	0.007
Diversifying	-0.003	0.599	0	0.000	0.435	1	0.047
Tender-offer	0.017	1.519	44	0.018	1.574	47	0.975
Serial acquirers	-0.002	0.278	0	0.002	0.307	0	0.007
Bidder PE	-0.015	1.011	11	-0.011	0.821	8	0.031
Sigma	0.075	2.957***	82	0.084	2.977***	72	0.019
Bidder number of analysts	-0.023	1.587	48	-0.017	1.177	32	0.676
Bidder run-up	0.059	1.956*	64	0.058	2.220**	65	0.181
Bidder age	0.013	1.195	28	0.008	0.734	14	0.005
Competing	-0.004	0.380	0	-0.004	0.376	1	0.581
Deal attitude	-0.005	0.593	0	-0.004	0.528	0	0.367
Transaction value	-0.019	1.924*	52	-0.037	2.470**	61	0.000
Mixed offer	-0.003	0.546	8	-0.003	0.510	10	0.661
Bidder Tobin's Q	-0.021	1.147	27	-0.009	0.866	13	0.008
Cash	-0.037	2.034**	77	-0.027	1.358	37	0.000
Free cash flow	0.012	0.710	11	0.020	0.995	25	0.000
Operating cash flow	-0.019	1.174	24	-0.021	1.136	25	0.746
Leverage	-0.015	0.976	20	-0.009	0.866	22	0.019
Capital expenditure	-0.028	1.698*	54	-0.022	1.307	31	0.005
Tangible assets	0.001	0.968	11	0.000	0.797	6	0.499
Sales growth	-0.020	1.225	32	-0.016	1.048	21	0.022

R&D expense	-0.015	0.755	10	-0.008	0.719	4	0.014
Inside ownership	0.014	1.022	24	0.014	0.923	23	0.542
Bidder illiquidity	0.086	3.576***	73	0.090	2.436**	66	0.993
Bidder efficiency	-0.011	1.182	31	-0.009	0.885	17	0.345
Bidder managerial ability	-0.033	1.466	40	-0.026	1.190	28	0.245
Bidder efficiency ranking	-0.006	0.543	12	-0.003	0.641	10	0.057
Bidder managerial ability ranking	0.006	0.845	17	0.013	1.003	27	0.003
Acquirer's rating existence	-0.024	1.403	45	-0.028	1.620	49	0.001
Herfindahl index	0.014	1.148	18	0.012	1.017	11	0.046
High-tech deal	-0.035	2.358**	82	-0.029	1.839*	60	0.013
Initial industry bidder	0.025	1.875*	67	0.022	1.739*	58	0.041
Sin industry dummy	-0.005	0.552	1	-0.006	0.816	6	0.375
Merger waves	-0.010	0.821	14	-0.015	(0.838	14	0.000
Market valuations	0.058	3.860***	96	0.059	3.909***	94	0.979
M&A liquidity	-0.002	0.356	1	-0.001	0.414	0	0.347
Policy uncertainty	0.005	0.628	13	0.002	0.753	10	0.714
Geopolitical risk	0.030	2.065**	78	0.024	1.310	32	0.000
Interest rate spread	-0.002	0.531	5	-0.005	0.623	5	0.098
Target advisors	-0.004	1.015	22	-0.012	1.254	35	0.021
Bidder advisors	0.007	0.892	15	-0.007	1.070	29	0.000
Regulation-deregulation	0.011	0.730	0	0.014	0.905	5	0.013
Earnings growth forecasts	0.012	0.799	8	0.010	0.810	13	0.873
Target's number of analysts	-0.053	4.255***	99	-0.056	4.385***	100	0.068
Dividend	-0.013	1.025	25	-0.015	1.073	30	0.090

Note: This table reports median values of estimated effects of target variables, one at a time, over 100 permutations of randomly selected twenty controls. The results of OLS are in Columns (1)-(3) and those of DML are reported in Columns (4)-(6). Columns (3) and (6) illustrates the percentage of significant effect of each variable at the 10% level over 100 repetitions. P-values of the Welch two sample t-test to test the differences of estimated effects between OLS and DML are reported in the last column. In DML, nuisance functions are learned by gradient boosting method (GBM). Absolute values of median t-statistics are reported. Heteroskedasticity-robust clustered standard errors at firm level are utilized to calculate t-statistics based on White (1980) and Chiang et al. (2022) in OLS and DML, respectively. Dependent variable is $CAR(-4,4)$. Variable definitions are provided in Appendix 3.2. *, ** and *** denote significance at the 10%, 5% and 1% respectively.

Figure 3.2 t-statistics derived from DML analysis using random benchmarks: CAR(-4,4)



Note: This figure illustrates the absolute values of t-statistics derived from DML analysis using 100 permutations of randomly selected twenty controls for each variable. Dependent variable is $CAR(-4,4)$.

Tables 3.8 presents the DML estimation results with LASSO and regression trees for $CAR(-1,1)$. The results show that transaction value and high-tech deal are the only variables identified by DML w. LASSO that exhibit a significant effect on abnormal return. These two variables are also among the important variables identified by GBM in our main analysis. However, we find no evidence to support the significant effects of target advisors, bidder advisors, and target's number of analysts. This inconsistency may be because LASSO is relying on the linearity assumption, while GBM considers the potential nonlinearity relationship between variables. Nevertheless, DML w. RT introduces these three variables with significant effect on $CAR(-1,1)$.

Table 3.8 DML results with alternative machine learners: CAR(-1,1)

Group name	Targets	(1) # of obs.	(2) DML w. LASSO	(3) DML w. RT
Bidder characteristics	Serial acquirers	11,113	-0.015	-0.018
	Bidder PE	11,113	-0.003	-0.006
	Sigma	11,113	0.021	0.020
	Bidder number of analysts	11,113	-0.015	-0.029*
	Bidder Run-up	11,113	-0.033	-0.034
	Bidder age	11,113	0.023	0.015
Deal-specific variables	Competing	11,113	0.006	0.004
	Deal attitude	11,113	-0.001	0.004
	Transaction value	11,113	-0.050***	-0.029
	Mixed offer	11,113	0.013	-0.001
Accounting variables	Bidder Tobin's Q	7,351	-0.037	-0.051
	Cash	7,351	-0.019	-0.014
	Free cash flow	7,351	-0.020	-0.027
	Operating cash flow	7,351	-0.031	-0.019
	Leverage	7,351	0.005	0.008
	capital expenditure	7,351	-0.023	-0.030
	Tangible assets	7,351	-0.007	-0.013
	Sales growth	7,351	-0.012	-0.006
	R&D expense	7,351	-0.031	-0.030
Other bidder characteristics	Inside ownership	5,412	0.000	0.008
	Bidder illiquidity	5,412	-0.006	0.025
	Bidder efficiency	5,412	-0.012	-0.049**
	Bidder managerial ability	5,412	-0.010	-0.027
	Bidder efficiency ranking	5,412	-0.032	-0.041
	Bidder managerial ability ranking	5,412	-0.001	-0.014
	Acquirer's rating existence	5,412	-0.003	-0.037
Industry characteristics	Herfindahl index	5,379	0.017	0.018
	High-tech deal	5,379	-0.043*	-0.036
	Initial industry bidder	5,379	0.021	0.020
	Sin industry dummy	5,379	-0.007	-0.010
Market characteristics (Related to M&As)	Merger waves	5,379	0.015	0.011
	Market valuations	5,379	0.029	0.022
	M&A Liquidity	5,379	0.013	0.007
Other market characteristics (Other macros)	Policy uncertainty	5,339	0.001	0.011
	Geopolitical risk	5,339	0.017	0.023
	Interest rate spread	5,339	0.018	0.033
Advisors	Target advisors	5,339	-0.005	-0.041**
	Bidder advisors	5,339	-0.006	-0.061**
Other variables	Regulation-deregulation	3,549	0.011	0.025
	Earnings growth forecasts	3,549	0.001	0.022

	Target's number of analysts	3,549	-0.057	-0.065**
	Dividend	3,549	-0.017	-0.018

Note: This table reports the estimated effects of targets on 3-day cumulative abnormal return, $CAR(-1, 1)$, using double machine learning method (DML) with four-fold cross-fittings. Nuisance functions are learned by LASSO and regression trees (RT) in Columns (2) and (3), respectively. P-values are adjusted using Hochberg (1988) correction for valid simultaneous inference. Heteroskedasticity-robust clustered standard errors at firm level are utilized to calculate t-statistics based on Chiang et al. (2022). The controls for the first group are relative size, target status, tender-offer, diversifying, bidder market-to-book value, method of payment, and bidder size. The controls for the second group are the union of the controls and the targets in the first group, and so on. *, ** and *** denote significance at the 10%, 5% and 1% respectively. Variable definitions are provided in Appendix 3.2

Considering $CAR(-4, 4)$ as the merger performance proxy in Table 3.9, we find more concordance between the results of LASSO and GBM. Specifically, six out of nine significant effects (i.e., transaction value, bidder Tobin's Q, high-tech deal, market valuations, geopolitical risk, target's number of analysts) identified by GBM are also introduced as important predictors by LASSO.

Table 3.9 DML results with alternative machine learners: CAR(-4,4)

Group name	Targets	(1) # of obs.	(2) DML w. LASSO	(3) DML w. RT
Bidder characteristics	Serial Acquirers	11,113	-0.001	-0.004
	Bidder PE	11,113	0.005	0.001
	Sigma	11,113	0.049**	0.028
	Bidder Number of Analysts	11,113	0.006	-0.021
	Bidder Run-up	11,113	0.014	0.013
	Bidder age	11,113	0.025**	0.011
Deal-specific variables	Competing	11,113	-0.006	0.000
	Deal Attitude	11,113	-0.007	0.000
	Transaction Value	11,113	-0.031**	-0.015
	Mixed offer	11,113	-0.015	-0.012
Accounting variables	Bidder Tobin's Q	7,351	-0.055*	-0.046
	Cash	7,351	-0.038	-0.032
	Free Cash Flow	7,351	0.032	0.046
	Operating cash flow	7,351	-0.009	-0.012
	Leverage	7,351	0..013	0.010
	capital expenditure	7,351	-0.017	-0.006
	Tangible assets	7,351	0.009	0.008
	Sales Growth	7,351	0.000	0.035
	R&D expense	7,351	-0.036	-0.040
Other bidder characteristics	Inside ownership	5,412	0.008	0.021
	Bidder illiquidity	5,412	0.112***	0.070
	Bidder efficiency	5,412	0.021	-0.016
	Bidder managerial ability	5,412	0.013	-0.001
	Bidder efficiency ranking	5,412	0.018	-0.008
	Bidder managerial ability ranking	5,412	0.028	0.017
	Acquirer's rating existence	5,412	-0.027	-0.039
Industry characteristics	Herfindahl index	5,379	0.007	0.020
	High-tech deal	5,379	-0.046**	-0.042
	Initial industry bidder	5,379	0.026	0.024
	Sin industry dummy	5,379	-0.014	-0.011
Market characteristics (Related to M&As)	Merger waves	5,379	0.007	0.010
	Market valuations	5,379	0.046**	0.050**
	M&A liquidity	5,379	0.009	-0.004
Other market characteristics	Policy uncertainty	5,339	0.002	0.012
	Geopolitical Risk	5,339	0.051***	0.048**

(Other macros)	Interest rate spread	5,339	-0.010	-0.006
Advisors	Target advisors	5,339	-0.023	-0.031*
	Bidder advisors	5,339	-0.002	-0.039**
Other variables	Regulation-deregulation	3,549	0..029	0.030
	Earnings growth forecasts	3,549	-0.022	0.004
	Target's number of analysts	3,549	-0.066***	-0.034
	Dividend	3,549	-0.021	-0.033

Note: This table reports the estimated effects of targets on 8-day cumulative abnormal return, $CAR(-4, 4)$, using DML with four-fold cross-fittings. Nuisance functions are learned by LASSO and regression trees in Columns (2) and (3), respectively. P-values are adjusted using Hochberg (1988) correction for valid simultaneous inference. Heteroskedasticity-robust clustered standard errors at firm level are utilized to calculate t-statistics based on Chiang et al. (2022). The controls for the first group are relative size, target status, tender-offer, diversifying, bidder market-to-book value, method of payment, and bidder size. The controls for the second group are the union of the controls and the targets in the first group, and so on. *, ** and *** denote significance at the 10%, 5% and 1% respectively. Variable definitions are provided in Appendix 3.2.

In summary, the results of this section qualitatively support our main findings on the importance of information-related variables in explaining the short-run abnormal returns.

3.6 Implications

Two primary research implications are suggested by this chapter. First, it introduces a novel set of factors that consistently exhibit significant effects. These factors are recommended additions to the commonly employed variables in predictive models. The intention is to enhance the predictive accuracy of models when assessing the influence of a new predictor in future studies focused on elucidating M&A returns. Unlike the well-established benchmarks in asset pricing literature, such as the Fama-French three-factor or the Carhart four-factor models (Carhart, 1997; Fama and French, 1993), the M&A literature lacks widely accepted benchmarks for analyzing the impact of new predictors on M&A returns. The analysis conducted in this chapter highlights the statistical significance of specific variables, including the number of analysts associated with the target, target advisors, and bidder advisors beyond the common determinants like relative size, target status, method of payment, etc. Given the consistent contributions of these variables, the chapter suggests that future studies should adopt a benchmark that combines these identified significant factors with the commonly used determinants. By controlling the impact of this combination, researchers can instill greater confidence in their assessments of the potential contribution of a new predictor for M&A deal short-term performance.

Second, this chapter underscores the imperative to formulate new theories in the field of M&A. The DML analysis undertaken unveils a notable finding—several predictors previously examined in other studies lack substantial information for predicting M&A returns beyond what is encompassed by commonly considered factors. This is consistent with the prevalence of irrelevant predictors in the M&A literature pointed out by King et al (2004). The identification of redundant predictors emphasizes the need for a more discerning approach in selecting variables for future studies, promoting the exploration of factors that genuinely contribute to accurate post-merger performance predictions. Consequently, researchers are encouraged to reevaluate existing frameworks and delve into novel avenues for theory-building in the context of M&A.

3.7 Conclusion

In this study, we exploit doble machine learning procedure of Chernozhukov et al. (2017, 2018) to assess the contribution of M&A return determinants beyond the commonly used predictors. We document the prevalence of irrelevant predictors in M&A literature; Implying that numerous variables proposed in the literature do not make a substantial contribution to the conventional variables in predicting merger performance.

We conclude that variables like target's number of analyst, target advisors, and bidder advisors should be used as benchmarks, along with commonly used variables, in examining the contribution of a new predictor for explaining M&A returns in future studies. Indeed, a hurdle we encountered during this study was the absence of a suitable foundation in the literature akin to that employed in the research conducted by Feng et al. (2020), i.e., Fama-French four factor model. We hope that our results will serve as a cornerstone for future research.

Chapter 4: Heterogeneous impacts of cost of carry on corporate money demand[33]

4.1 Introduction

Traditionally, to influence and stabilize the market, monetary policy has been employed as a potent tool by governments and regulators. It stands as a crucial instrument through which authorities address economic crises. Among its various mechanisms, the interest rate emerges as the most dynamic tool, playing a dual role by passively curbing inflation, actively influencing government reserves, and aiding fiscal policy (Davig and Leeper, 2011; Fatás & Mihov, 2003).

A conventional long-term money demand function establishes a connection between the demand for money, real economic transactions and the opportunity cost associated with holding money balances. The last component, i.e., the opportunity cost of holding money, is mostly measured by interest rates. In the field of monetary economics, a persistent area of focus has been the elasticity of money demand to fluctuations in interest rates (e.g., Lucas and Nicolini, 2015; Meltzer, 1963). Insights into how money demand reacts to variations in the interest rate can assist in quantifying the welfare gains from a low inflation rate (e.g., Berentsen et al., 2015; Ireland, 2009; Lucas, 2000; Teles and Zhou, 2005). The stability of the relationship between money and interest rates is essential for the effective monitoring and targeting of monetary aggregates. When a central bank exercises control over money balances, it gains the ability to influence macroeconomic policy. The success of such policy interventions hinges on the presence of a consistent relationship between money demand and its determinants. If the demand for money is unstable, the effectiveness of monetary policy becomes limited, and its role in shaping economic outcomes diminishes (Lee and Chien, 2008).

The Baumol-Tobin model (Baumol, 1952; Tobin, 1956) suggests that opportunity cost negatively affects money demand. However, recent empirical studies cast doubt on a such pervasive negative sensitivity. By introducing a new measure for opportunity cost, the so-called ‘cost of carry’, Azar et al. (2016) confirm that corporate liquidity management is negatively related with opportunity cost, consistent with theoretical predictions. By contrast,

[33] We gratefully acknowledge helpful comments from Susan Athey, Ruhollah Eskandari, Xiaodan Gao, and Erik Sverdrup. The time series of monetary policy shocks was kindly provided by Emi Nakamura.

Gao et al.'s (2021) findings suggest that this negative relation dominates only at times of high interest rates. They argue that in very low interest rate regimes, where the precautionary motive of holding cash is stimulated, the sensitivity of cash to the interest rate is positive. Such a direct relationship in times of low interest rates is also documented by Stone et al. (2018), who use a random effects threshold model. At a macro-economic level, Benati et al. (2021) also document that the empirical money demand curve does not follow the Baumol-Tobin theoretical model in countries experiencing very low interest rates, due to the different patterns of borrowing constraints in such environments. In addition to these mixed results, Bates et al. (2009) and Graham and Leary (2018) document some evidence that interest rates are uncorrelated with cash holdings.

The aim of this chapter is to understand and uncover the underlying mechanism that creates these seemingly contradictory results. We adopt an approach that allows an evaluation of the money demand function at an individual firm level. At an aggregate level, the average relationship between corporate cash and cost of carry across all firms is negative and consistent with traditional theories. However, the story is completely different at the individual firm level, especially in the low interest rate regions. Despite the average negative effect, we document significant heterogeneity in the cost of carry effect on cash holdings at firm level, ranging from positive to neutral or negative effects.[34] In other words, the major distinction of this study compared to abovementioned studies is that we investigate *firm-level* sensitivity of cash to the cost of carry instead of looking at an average estimation for the entire population.

Our motivation for exploring individualized effects, rather the average effect, stems from the fact that firms differ enormously in their characteristics and liquid assets composition (e.g., Cardella et al., 2021; Duchin et al., 2017); consequently, the same aggregate monetary policy may affect firms' cash holdings in different ways and magnitudes (heterogenous effects). This argument is consistent with emerging macroeconomic literature which tries to explain the transmission mechanisms of monetary policy to real economy based on the heterogeneity in individuals, e.g., households or firms, in the context of the heterogeneous agent model (e.g., Durante et al., 2022; Luetticke, 2021; Ottonello and Winberry, 2020).[35]

[34] Understanding treatment effect of heterogeneity can be useful for the evaluation of policy effectiveness and the validation of theories under consideration (for further discussion, see Abadie and Cattaneo (2018) and Athey and Imbens (2017)).

[35] For example, in answering the question "which firms are the most responsive to changes in monetary policy?", Ottonello and Winberry (2020) find that investment decisions made by firms with low default risk are more responsive to monetary policy shocks, proxied by Fed Funds Rate (FFR), than those made by firms

This chapter exploits a new supervised machine learning method, i.e., the causal forest (Athey and Imbens, 2016; Wager and Athey, 2018; Athey et al., 2019), to flexibly study firm-level heterogeneity in the response of firms' liquidity to cost of carry changes. The causal forest method was originally designed to estimate the granular heterogeneity in a treatment effect and, most importantly, identify latent subgroups in the target population that may be differently affected by a policy or intervention, conditional on observable characteristics (Wager and Athey, 2018). Although conventional approaches can detect sub-populations that have different treatment effects, they encounter various technical challenges. First, interacting treatment variable indicators with baseline covariates raises concerns about data snooping bias in a multiple hypothesis testing framework. This is even more pronounced in high-dimensional settings, which may lead to spurious findings (Davis and Heller, 2020; Wager and Athey, 2018). Second, partitioning the data into pre-specified subgroups based on specific variables and estimating a single model in separate subsamples prevents the identification of unknown subgroups and developing new theories (Davis and Heller, 2017). Moreover, these two approaches (i.e., interacting treatment variable indicators and partitioning the data) necessitate parametric assumptions that are unlikely to be held in many practical applications (Miller, 2020). The causal forest is a convenient nonparametric method to address these challenges while inheriting desirable properties from regression forests, such as stability (Athey et al., 2019).

The chapter estimates the sensitivity of cash holdings to the cost of carry using annual data from a large panel of non-utility and non-financial US firms over the past five decades (158,429 firm-year observations covering the period 1971-2019). Our main finding suggests that the effect of the cost of carry on corporate liquidity is substantially heterogeneous across individual firms. More precisely, while for most firms in the sample, cash holdings are negatively affected by the cost of carry, which is in line with theoretical predictions, there is a substantial fraction of firms that experience a positive or neutral effect. This result is robust to alternative measures of cash holdings and is not driven by omitted variables bias. The heterogeneity in the cost of carry effect implies that an overall effect estimation obtained from traditional regression models is of limited value for the cash-opportunity cost link and may provide limited guidance for monetary policy evaluation. This is because traditional models in prior studies examine the average cash-opportunity cost relationship across all

with high default risk. Similarly, in essence, we show that corporate liquidity management in large firms and those with low net working capital is more responsive to cost of carry.

firms, instead of estimating the relationship at the individual firm level. As a result, they ignore the full range of effects and produce mixed empirical relations.

Second, we explore the determinants of heterogeneity in the cost of carry effects. Importance scores analysis, confirmed by the best linear projection analysis, suggests that firm size is by far the main source of the heterogeneity, such that approximately 50% of heterogeneity is related to this covariate. This finding confirms the importance of the role of economies of scale in the transaction cost model. Net working capital has the second largest contribution (approximately 17%) in driving heterogeneity.

Third, we implement the Generalized Additive Model (GAM) on the firm-level estimated effects to identify subgroups of firms whose cash reserves are differently affected by the opportunity cost measure. We document a hump-shaped effect of firm size on the elasticity of cash to the cost of carry. Moving from the left tail of the firm size distribution (small firms), the sensitivity of cash initially decreases (in absolute value) with firm size. It then increases almost from the median of the distribution towards the right tail of the distribution (large firms). In relation to net working capital, which is the second most important factor, sensitivity of cash to the cost of carry decreases with net working capital.

To enhance our knowledge of the observed heterogeneity in the corporate money demand, we conduct several additional analyses. First, to understand the dynamics of the heterogeneity effect over time, we employ the causal forest algorithm cross-sectionally over five decades (i.e., 1970s, 1980s, 1990s, 2000s, and 2010s). The results reveal that heterogeneity has become more pronounced over decades. Chronologically, this coincides with the lifting of the Regulation Q in the banking sector in the early 1980s.[36] We also provide evidence that, in contrast to theoretical predictions, positive elasticity of cash to the cost of carry is evident from the 1990s onward, which can be attributed to the advent of the sweep account programs in the first half of the 1990s.[37] Banking deregulation in the 1980s and the introduction of financial innovations in the 1990s reduced the cost and time of access to cash and drove firms to manage their liquidity needs differently from what traditional

[36] As a macroprudential policy between 1933 and 1986, the Federal Reserve imposed interest rate ceilings on time and savings deposits and prohibited paying interest rate on demand deposits, called Regulation Q (Azar et al., 2016; Koch, 2015). The Deregulation Act 1980 gradually eliminated all interest rate ceilings, and finally completed in March 1986, to tackle the dramatic rise in inflation in the late 1970s and early 1980s – the era of the Great Inflation (Koch, 2015). For details on the phasing out of Regulation Q, see Gilbert (1986).

[37] Under the retail sweep programs, since 1994, commercial banks automatically move the balances in checkable deposits just prior to the close of business into money market deposit accounts (MMDAs) and transfer back from MMDA when necessary. These financial transfers are either done only at the weekend or based on a pre-determined target level (Anderson, 1997; Teles and Zhou, 2005). Bank's ability to manipulate sweeping activity, however, is limited due to several reasons (See, for example, Curfman and Kandrac, 2022).

theoretical models dictate. Second, motivated by the deep effects of the 2008 global financial crisis on money markets, we find that the distributional impact of the cost of carry in the post-crisis era is statistically different from the pre-crisis one (based on a two-sample Kolmogorov-Smirnov test): the distribution is flatter, with a larger domain of effects in the post-crisis period in lieu of a more concentrated one in the pre-crisis. Finally, exploring the heterogeneity by industry indicates that the retail trade sector is the most homogeneous group in cash management in response to the opportunity cost changes, with more concentrated firm-level effects around the average effect, in comparison to manufacturing, services, and other industries.

Our study makes several novel contributions to different strands in literature. First, we explain the opposing evidence presented in the literature (e.g., Azar et al., 2016; Gao et al., 2021). Our firm-level estimation results show that despite an averagely negative relation between cash and opportunity cost, which is in line with Azar et al. (2016), it is only in recent years that some firms experience a positive relationship between these two variables, which are essentially characterized by very low interest rates. The likelihood of observing positive effects of the cost of carry on cash holdings is higher in the region of low interest rates, in comparison to the region of high interest rates (9.818% for the 2010s, in contrast to 0.003% and 0% for the 1990s and the 1970s, respectively).

Second, if we interpret the increasing heterogeneity as a sign of instability, we contribute to a large body of work on money demand stability from a novel perspective. There is a significant literature on money demand stability in monetary economics, dating back to Meltzer (1963) and including more recent studies such as Benati et al. (2021) and Lucas and Nicolini (2015), among others. By quantifying the heterogeneous impact of the cost of carry on cash holdings, we provide evidence that the widening range of distributional impacts of the cost of carry started to increase in the 1980s. It has been exacerbated since the 1990s, when the density of effects started moving into the positive territory. These are consistent with the view that regulatory changes in the late 1970s (i.e., lifting Regulation Q) and financial innovation in the first half of the 1990s (i.e., the introduction of retail deposit sweep programs), perhaps 'irredeemably' destroyed the long-lasting relation between money demand and interest rate (Belongia and Ireland, 2015; Berentsen et al., 2015; Lucas and Nicolini, 2015).

Third, we contribute by examining the role of firm characteristics in the relationship between cash holdings and opportunity cost, an aspect that has been ignored in prior studies, perhaps due to the lack of relevant theories or low statistical power (Azar et al., 2016; Gao et al., 2021).[38] We add to the findings of Eskandari and Zamanian (2022), who compare the link of the cost of carry and cash holdings between financially constrained and unconstrained firms as proxied by their payout ratio, firm size, debt rating, and Kaplan-Zingales index. By partitioning their data into two subsamples and applying a parametric model, they could not explain how the sensitivity of cash to cost of carry *gradually* changes with firm size. While we confirm that the effect of the cost of carry on cash holdings is greater (in absolute value) for unconstrained firms (large firms), our causal forest estimation results indicate that the effect of firm size on this relationship has a quadratic effect rather than a simple linear one. In addition to firm size, we empirically assess the role of other common cash holdings determinants (e.g., financial leverage, growth opportunities, etc.) in driving the heterogeneity of the cost of carry effect.

Fourth, to the best of our knowledge, our article is the first in the cash holdings literature to examine the cash-opportunity cost sensitivity by employing the causal forest method. Our chapter thus makes an important methodological contribution by highlighting new applications of the causal machine learning tools in the domain of corporate finance. In this regard, this chapter relates to recent empirical studies which take advantage of the capabilities of the causal forest procedure in financial analysis (e.g., Gulen et al., 2020; Labro et al., 2022; Li et al., 2021; Stein, 2022).

The remainder of the chapter is structured as follows. In Section 2, we review related literature. Section 3 introduces the causal forest method. Section 4 describes data. Sections 5 and 6 presents results, and Section 7 concludes.

4.2 Related literature

4.2.1 Opportunity cost and cash holdings

The transaction model suggests that opportunity cost negatively affects money demand (e.g., Baumol, 1952; Tobin, 1956). In this classical economic model, opportunity cost is mainly measured by nominal interest rates.[39] A decrease in the risk-free interest rate lowers the opportunity cost of holding cash and, hence, induces firms to build cash as a buffer against future cash flow shocks as well as to meet current needs (Azar et al., 2016; Bates et al.,

[38] Regarding the relevant theories, Azar et al. (2016) assert that "*we are not aware of theories predicting a different sensitivity of cash holdings to cost of carry for different firm characteristics*" (p. 2220). Regarding statistical power, Gao et al. (2021) state that "*While it would be interesting to explore the source of this sign change by examining interactions with observable variables, we do not have enough statistical power to uncover any significant results*" (p. 1849).

[39] For a historic review on the role of interest rate in monetary policy, see Belongia and Ireland (2015).

2009). This cash stockpile also allows firms to negotiate lower real interest payments and obtain better borrowing rates when they need external funds (Gao et al., 2021). By contrast, in high interest rate regimes when credit conditions are tighter, the cost of financing increases (Erel et al., 2021). As a result, firms use internal resources, in lieu of relying on expensive external finance, for transaction purposes, leading to a reduction in cash reserves.

Empirical evaluation of the association between the interest rate and corporate liquidity has been the subject of many studies in recent years. By defining the cost of carry as a new proxy for the cost of holding cash instead of raw interest rate, Azar et al. (2016) document that changes in corporate cash holdings can be explained by the cost of carry in the US and other international capital markets (Japan, Italy, Germany, the UK, France, and Spain). Their results show a strong negative relation between the cost of carry and corporate cash demand, which is stable over time based on rolling regressions.

Contradicting the traditional view of an inverse relation between interest rate and money demand, Gao et al. (2021) document a hump-shaped relation between these two constructs. They attribute the observed pattern to the relative importance of the precautionary and opportunity cost motives. At low interest rates, when precautionary motives are stronger, corporate cash rises with the risk-free rate. After reaching a peak, it then declines, when the opportunity cost motive dominates. To support the results, they use both real and nominal rates for different measures (3-month T-bill, 1-year TCMR, 5-year TCMR, 10-year TCMR, and Federal funds rate). We differ from Gao et al. (2021) in at least two directions. First, our goal is not to examine the linear or nonlinear effect of opportunity cost proxies (interest rates or cost of carry) on corporate cash. Rather, we dissect the heterogeneity in the cost of carry effect at firm level. By doing this, not only do we have a comprehensive picture of the relation between cash and opportunity cost, but we can also detect the smallest changes in this empirical relationship between and within firms. Second, and more important, using these individualized effects, we can mine the data space to identify the underlying mechanisms of cost of carry effects of different magnitudes, while performing such an analysis using traditional regression models is associated with technical challenges, as discussed earlier.

Mulligan (1997) estimates the empirical relation between cash balances and interest rate. Mulligan’s findings show that the elasticity of cash to different measures of interest rates (Moody’s AAA corporate bond yield, 3-month T-bill rate, 6-month commercial paper rate, 6-month T-bill rate) is negative. Stone et al. (2018) use a random effects threshold model and find no evidence to support the negative relation between corporate cash holdings and interest rate. By contrast, they report a positive relationship between cash holdings and interest rate, at different quantiles of cash holdings, and argue that this positive-sloping curve better describes the elasticity of cash in modern times. In an attempt to describe the observed positive effect, they fail to attribute it to the tax cost of repatriating earnings, pension fund contributions, zero-leverage firms, financial constraints, high-tech industries, and weak corporate governance. They conclude that "*a revised theory of the relationship between interest rates and cash holdings may be warranted*" (p. 33).

Ysmailov (2021) attributes the previous inconclusive results on the cash-interest rate nexus to the measurement error in cash. He shows that the use of different proxies, such as short-term investment, cash, or the sum of these two components to measure the liquidity of firms, generates contradictory results. The author's empirical results suggest that firms follow a two-step procedure in their liquidity management. First, at the top level, firms determine their total amount of cash in a converse relation with interest rates, while at a lower level, they decide on the composition of their liquidity portfolio.

The above studies fail to account for the heterogeneous effect of opportunity cost proxies. Interest rates are likely to have a heterogeneous impact on cash holdings as firms differently determine their cash position, especially after the lifting of Regulation Q in the late 1970s and early 1980s and under new financial innovations (Azar et al., 2016; Cardella et al., 2021; Gao et al., 2021). The opportunity cost of cash for firms with a higher fraction of non-interest-bearing assets is higher than for firms with a higher level of cash in interest-bearing assets (Azar et al., 2016). Consequently, money demand could be influenced non-homogeneously by monetary policy shift across individual firms. We aim to fill this gap by estimating the heterogeneity in the cash-cost of carry sensitivity at firm level by exploiting new advancements in causal machine learning methods, i.e., the causal forest method proposed by Wager and Athey (2018) and further refined in Athey et al. (2019).

4.2.2 Applications of causal forest

The causal forest procedure has attracted considerable attention over different scientific fields in recent years. In this section, we briefly review some applications of this method in finance and economics. Gulen et al. (2020) utilize the causal forest algorithm to investigate the effect of debt covenant violations, a binary variable equal to one if the firm is in default and zero otherwise, on corporate investment. The authors show that detection of heterogeneity in the effect of covenant violations on investment is an important issue in resolving the contradictory results in the debt covenant literature. They emphasize that producing a range of effects rather than a local average treatment effect is one of the main advantages of the causal forest relative to other methods for making causal inference, such as a regression discontinuity design.

Li et al. (2021) employ the causal forest procedure to investigate the heterogeneous effect of the COVID-19 pandemic on industry indices in the Chinese capital market. Their findings show that the leisure (such as catering and tourism) and media (such as movies) industries were most affected by the COVID-19 pandemic in the early days. Their findings also show that the heterogeneity of industries affected by the COVID-19 pandemic weakened during the outbreak.

Stein (2022) assesses the effect of the 'one-female-board-member' policy on the revenues of Indian firms during the COVID-19 pandemic. Stein compares the estimation results of a Difference-in-Difference (DID) analysis with that of the causal forest method. The result of DID shows that compliance with the policy positively affects the revenues during the COVID-19 crisis. By contrast, the results of the causal forest show the heterogeneous effect of board gender diversity on crisis revenues, such that positive and negative effects of female directors are observed in the sample. Some firms also experience no significant effect. He concludes that deeply understanding the heterogeneous impact of board gender diversity is crucial to evaluating the effectiveness of the policy.

The causal forest approach has also been widely adopted to explore the heterogeneity in a target variable across different economic areas. Carlana et al. (2022) evaluate the effectiveness of a new program, namely Equality of Opportunity for Immigrant Students, developed for steering immigrant students towards high schools that better match their academic abilities in Italy. Noting that partitioning the sample and applying a parametric model (as a common approach for subgroup analysis) may increase the probability of Type I errors, they employ the causal forest method to detect un-prespecified groups of students who may take advantage of this program. Their findings show that male and female students from a low socioeconomic background benefited from the intervention. They argue that the identified heterogeneity could be used for future targeting.

Finally, Davis and Heller (2020) utilize the causal forest method to analyse the heterogeneous impacts of youth summer job programs to identify who benefits most from these programs, making it possible to determine optimal allocation, in Chicago. They find that, unlike the standard interaction approach, the causal forest successfully detects the heterogeneity in the employment impacts.

4.3 Methodology: The causal forest

We utilize causal forest to study the heterogeneity in the cost of carry effect on corporate cash holdings. Causal forest is a machine learning non-parametric method, developed in a series of papers by Athey and Imbens (2016), Wager and Athey (2018), and Athey et al. (2019). It has several advantages over traditional causal inference approaches (e.g., interacting and partitioning) in determining latent subgroups of a population differently affected by a treatment, such as not suffering from the theoretical limitations of parametric methods, and controlling false discovery rates (Davis and Heller, 2020; Miller, 2020; Wager and Athey, 2018). Furthermore, Wager and Athey (2018) and Athey et al. (2019) prove that the resulting estimator from the causal forest is asymptotically unbiased and normal. In addition, simulation studies conducted by Wager and Athey (2018) and Knaus et al. (2021) demonstrate the good performance of the causal forest estimator in detecting heterogeneous causal effects relative to other non-parametric methods, such as nearest-neighbour matching, etc.

Suppose we denote the dependent (response) variable, binary treatment (policy or intervention), and observable characteristics (or confounders) with Y_i, $W_i \in \{0,1\}$, and X_i, respectively, for subject $i = 1, \dots, n$. The potential outcomes for the ith subject if it is exposed (treatment group) or non-exposed (control group) to the treatment are denoted by $Y_i^{(1)}$, and , $Y_i^{(0)}$, respectively. The parameter of interest that could be used to summarize the individual-level treatment effect is the conditional average treatment effect (CATE), which is defined as (Wager and Athey, 2018):

$$\tau(x) = E[Y_i^{(1)} - Y_i^{(0)} | X_i = x]. \qquad (4.1)$$

The CATE provides a description of the heterogeneity of the treatment effect at individual level. To elaborate, using the CATE, the researcher can detect how the treatment effect varies with observables and identify individuals who respond differently to the treatment (Fan et al., 2022; Wager and Athey, 2018).

Wager and Athey (2018) develop CF as an unbiased estimator for the objective function $\tau(x)$. The CF approach divides the data into subgroups based on a set of observables X, and then estimates $\tau(x)$ using the following efficient estimator (Athey and Wager, 2019; Athey et al., 2019):

$$\hat{\tau}(x) = \frac{\sum_{i=1}^{n} \alpha_i(x)(Y_i - \widehat{m}^{(-i)}(X_i))(W_i - \hat{e}^{(-i)}(X_i))}{\sum_{i=1}^{n} \alpha_i(x)(W_i - \hat{e}^{(-i)}(X_i))^2} \tag{4.2}$$

where $\widehat{m}^{(-i)}$ and $\hat{e}^{(-i)}$ are the out-of-bag (OOB) predictions of the outcome expectation (i.e., $m(x) = E[Y_i|X_i = x]$) and the conditional treatment probability or the 'propensity score' of receiving treatment (i.e., $e(x) = \Pr[W_i = 1|X_i = x]$), respectively. The non-negative weights $\alpha_i(x)$ is a data-driven kernel that measures how often the ith training example falls in the same leaf as the test point x. In Equation (4.2), $m(x)$ and $e(x)$ are two nuisance functions through which confounders affect the dependent and treatment variables, respectively. Procedurally, the CF algorithm first separately estimates these functions, typically using regression forest (Tibshirani et al., 2021). Then it utilizes the OOB predictions from these two forests to obtain the corresponding residuals (i.e., $Y_i - \widehat{m}^{(-i)}(X_i)$, and $W_i - \hat{e}^{(-i)}(X_i)$). This residualization (or local centring) makes the CF estimation results robust to the effect of confounders, as this technique partials out the confounders effect before building the CF (Athey and Wager, 2019).

For a continuous treatment (like the cost of carry in this study), we have the conditional average partial effect, as a substitute for the conditional average treatment effect, which is given by (Athey et al. 2019; Tibshirani et al., 2021):

$$\tau_c(x) = \frac{Cov(W_i, Y_i|X_i = x)}{Var(W_i|X_i = x)} \tag{4.3}$$

where Cov (.) is the covariance between dependent and treatment variables, and Var (.) measures the variance of the treatment conditioning on observables. The CF estimator for the $\tau_c(x)$ is (Athey et al., 2019):

$$\hat{\tau}_c(x) = \frac{\sum_{i=1}^{n} \alpha_i(x)(Y_i - \bar{Y}_\alpha)(W_i - \bar{W}_\alpha)}{\sum_{i=1}^{n} \alpha_i(x)(W_i - \bar{W}_\alpha)^2} \tag{4.4}$$

where $\bar{W}_\alpha = \sum \alpha_i(x)W_i$, and $\bar{W}_\alpha = \sum \alpha_i(x)Y_i$. $\hat{\tau}_c(x)$ will be the estimated parameter of interest in the empirical application that follows.[40]

An underlying assumption for the validity of CATE's estimator is unconfoundedness (or conditional exogeneity), which states that differences in outcomes are attributable to the

[40] In a robustness check analysis, we replace the continuous treatment (cost of carry) with the binary one, defined by the median of cost of carry. In that estimation, we follow Equation (4.2). We obtain a similar pattern of heterogeneity in the relation between cash holdings and opportunity costs. These results are available upon request.

treatment, conditional on confounders (Wager and Athey, 2018). This assumption is more plausible in applications where the set of confounders is rich, with a large number of variables that may confound the relation between treatment and outcome (Fan et al., 2022). Our cofounders (X) set includes ten basic determinants, while we conduct a robustness test of six additional (thus sixteen) cofounders. More importantly, by averaging across 10-year lagged values, the cost of carry does not suffer from endogeneity problems in its relationship with corporate liquidity (Azar et al., 2016, p. 2205).

We implement the CF method using the R *grf* package (Tibshirani et al., 2021). Hyperparameters of the causal forest (e.g., number of variables tried for each split, maximum imbalance of a split, etc.) are chosen by 10-fold cross-validation (CV). To achieve better convergence properties, the CV is conducted on the *R*-learner objective function, proposed by Nie and Wager (2021). During the course of estimation, we set the minimum leaf size (number of observations in each tree leaf) to 5, and the number of trees to 2,000, as default in the package.

After estimating the heterogeneity of the cost of carry effect, we conduct a series of tests to evaluate the fit of the estimated causal forests. First, we run a test based on the best linear predictor (BLP) of Chernozhukov et al. (2018) to investigate whether the heterogeneity in the effect of cost of carry has been well calibrated by the fitted CF. This test is conducted by constructing the following linear regression model:

$$Y_i - \widehat{m}^{(-i)}(X_i) = \beta^C \bar{\tau}.\left(W_i - \hat{e}^{(-i)}(X_i)\right) + \beta^D\left(\hat{\tau}_c{}^{(-i)}(X_i) - \bar{\tau}\right)\left(W_i - \hat{e}^{(-i)}(X_i)\right) + \varepsilon_i \tag{4.5}$$

where $\hat{\tau}_c{}^{(-i)}(X_i)$ is the OOB causal forest estimates, obtained by Equation (4.4), and $\bar{\tau}$ is the average of these estimations. β^C and β^D measure the quality of average treatment effect and treatment effect heterogeneity, respectively. A significant positive coefficient on the second term of Equation (4.5) (i.e., β^D) demonstrates the success of the CF algorithm in unveiling heterogeneous effects (Athey and Wager, 2019). Second, we regress doubly robust scores of $\hat{\tau}_c$, derived from the CF, against a subset of covariates to produce the best linear projection of the CATE onto these covariates (Semenova and Chernozhukov, 2021). This second stage regression analysis is used to assess how the CATE is associated with the specific covariates (Tibshirani et al., 2021). The result of this test is presented like the traditional OLS method. Such that the estimated coefficients on the features can be interpreted as the effect of the corresponding covariate on the CATE. For more details of the CF approach, we refer readers to the *grf* package laboratory at GitHub (https://grf-labs.github.io/grf/).

4.4 Sample selection and variable definitions

4.4.1 Sample selection

To empirically investigate the heterogeneity in the cash-interest sensitivity, we utilize a large panel of US industrial firms. Annual firm-level financial data comes from the Compustat fundamental database.[41] We follow the common practice of prior literature in the process of sample selection criteria (e.g., Bates et al., 2009; Opler et al., 1999) and exclude financial (SIC code 6000-6999) and utility firms (SIC codes 4900-4999). We also drop firm-year observations with nonpositive book values of total assets and sales revenue. Missing values are removed at the final stage. The final sample consists of 158,429 firm-year observations from 17,062 unique firms.

Our sample covers the period of 1971-2019. Following Gao et al. (2021), we consider this period because the time series of the nominal 3-month T-bill rate displays two opposite features in this time interval, i.e., an upward trend during the 1970s and early 1980s, reaching the all-time high of 15.05% in 1981:Q2, and a downward trend after that, approaching the zero lower bond (ZLB) in recent years. This time span creates an ideal situation for us to examine how the heterogeneity changes in different interest rate environments. We obtain data for the nominal 3-month T-bill rate from the Federal Reserve Economic Data (FRED) database.[42]

4.4.2 Variables definition

Our dependent variable is corporate cash holdings. Following Azar et al. (2016), we focus primarily on the natural logarithm of cash and cash equivalent to net assets. For robustness check we also consider the cash-to-assets ratio as an alternative proxy (Bates et al., 2009; Gao et al., 2021).

The variable of interest which we want to examine is the opportunity cost of holding cash. A commonly used measure for opportunity cost in the corporate liquidity literature is the short-term interest rate, which is often proxied by the 3-month T-bill rate. The interest rates are associated with some drawbacks in measuring the opportunity costs. First, as a time-specific variable, they only measure the time value of money (e.g., Van Binsbergen et al., 2022). Second, and more important, they do not consider the cash composition of a firm in a given year. It is well documented that firms differ in how they determine the share of

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[41] In a robustness check analysis, where we examine the heterogeneity in the raw interest rate impact on cash holdings, we retrieve the quarterly data from Compustat to create an adaptable dataset with monetary policy shocks data from Nakamura and Steinsson (2018).

[42] For a detailed description of the interest rate movement from 1970 onward, see Stone et al. (2018).

interest-bearing and non-interest-bearing assets in their liquidity structure (Cardella et al., 2021); hence, firms with lower levels of non-interest-bearing assets are exposed to lower opportunity cost in times of high interest rates. Recent empirical analysis conducted by Ysmailov (2021) confirms that the raw interest rate may not be an ‘appropriate’ proxy for opportunity costs. To overcome these drawbacks, Azar et al. (2016) introduce the cost of carry as a two-dimensional proxy which incorporates both the short-term interest rate and cash composition in measuring the opportunity costs, as follows:

$$CC = \mathrm{T} - \mathrm{bill} \times \bar{s} \tag{4.6}$$

where T-bill is the nominal 3-month T-bill rate, and $\bar{s}$ is the lagged 10-year average of non-interest-bearing assets as a share of total cash and cash equivalents. According to Eskandari and Zamanian (2022), the larger the fraction of interest-bearing accounts, the more ‘informative’ the cost of carry for the opportunity cost of holding cash is compared to the simple T-bill rate.

We consider firm-specific variables commonly used in corporate cash literature (Bates et al., 2009; Opler et al., 1999) to account for covariates that may confound the relationship between cash holdings and cost of carry. This set of confounders includes firm size, market-to-book ratio, financial leverage, dividends, cash flow, cash flow volatility, R&D expense, net working capital, capital expenditures, and acquisitions. Variable definitions are provided in Appendix 4.1.[43]

Table 4.1 presents the summary statistics of cash proxies, cost of carry, and the confounders. On average, 15.4% of total assets are held in the form of cash and cash equivalents. This is consistent with 17.8% and 15.6%, values reported by Azar et al. (2016) and Ysmailov (2021), respectively. The opportunity cost of holding cash is about 3.2% with standard deviation of 2.6%. Descriptive statistics for confounders are generally in line with previous studies. For example, summary statistics for R&D expenditure indicate that firms invest on average 3.7% of their sales revenue in research and development (R&D) activities, which is very similar to the mean value of 2.7% in Opler et al. (1999).

Table 4.1 Summary statistics

Variable	N	Mean	SD.	Min.	Max.
Cash-to-assets	158,429	0.154	0.188	0.000	0.857

[43] In further analysis section, where we examine the influence of omitted variables bias on the heterogeneity of CC effect, we add six additional covariates to these benchmark confounders, including: industrial diversification, intangible assets, multinationality, tax costs of repatriating earnings, debt maturity, and tangible assets.

Cash-to-net assets	158,429	0.336	0.818	0.000	5.979
Cost of carry	158,429	0.032	0.026	0.000	0.114
Firm size	158,429	5.071	2.278	0.491	10.732
Market-to-book ratio	158,429	1.735	1.385	0.507	9.160
Financial leverage	158,429	0.226	0.183	0.000	0.717
Dividends	158,429	0.397	0.489	0.000	1.000
Cash flow	158,429	0.024	0.172	-0.894	0.261
Cash flow volatility	158,429	0.087	0.051	0.017	0.226
R&D expenditures	158,429	0.037	0.583	0.000	0.485
Net working capital	158,429	0.109	0.195	-0.418	0.571
Acquisitions	158,429	0.019	0.053	-0.002	0.321
Capital expenditure	158,429	0.065	0.068	0.000	0.367

Note: This table reports the summary statistics of variables. The sample consists of 158,429 firm-year observations from 17,062 unique firms retrieved from Compustat over 1971-2019. Financial (SIC code 6000-6999) and utility firms (SIC codes 4900-4999) are excluded. To mitigate the influence of outliers, we winsorize all variables at the 1st and 99th percentiles. Variable definitions are provided in Appendix 4.1.

4.5 The results

4.5.1 The heterogeneous impacts of cost of carry

To illustrate the heterogeneity of the cost of carry effect on corporate cash holdings, we examine firm-level effects, which are estimated by the causal forest method over the full sample period (1971-2019). Due to the panel structure of our dataset, following Athey and Wager (2019), we utilize a cluster-robust (by firm) version of causal forest. For robustness, we employ two different measures of cash holdings, such as the logarithm of cash-to-net assets ratio and the cash-to-assets ratio. We employ ten commonly used cash holdings determinants which are firm size, market-to-book ratio, financial leverage, dividends, cash flow, cash flow volatility, R&D, net working capital, capital expenditures, and acquisitions as confounders in the process of the tree growth in the forest.

Table 4.2 presents the summary statistics of the estimated effects of cost of carry. The main overall findings show that cost of carry has an average negative effect on the cash measures (-9.002 and -0.668, with standard deviations of 5.162 and 0.416 respectively). However, a notable finding suggests that, in contrast to the average negative effect, the maximum value of the estimated effects is positive (8.427 and 1.661 for the log of cash-to-net assets and cash-to-asset ratios, respectively). In fact, the causal forest method enables us to investigate the effect of a variable of interest with a more granular view, in addition to a general perspective. To elaborate, by considering firm-specific outcome expectation and propensity score (i.e., $m(x_i)$ and $e(x_i)$, respectively), the causal forest approach generates individualized estimations of cost of carry effects which can be used to detect subgroups of firms with heterogenous effects, which would not have been possible by employing traditional regression models and using an overall effect estimation for the entire population.

The last two columns report the result of the best linear predictor (BLP) test, proposed by Chernozhukov et al. (2018), which formally tests the significance of the detected heterogeneity of the cost of carry effect. A positive and significant coefficient β^D is an indication of the goodness of fit of the estimated forest, and it also suggests that the causal forest succeeds in detecting heterogeneity (Athey and Wager, 2019). The results strongly indicate that the estimated model is well calibrated to unveil heterogeneity for the cost of carry effect (Sig.<0.01). This is robust to different cash holding proxies.

Table 4.2 Heterogeneous effect of cost of carry

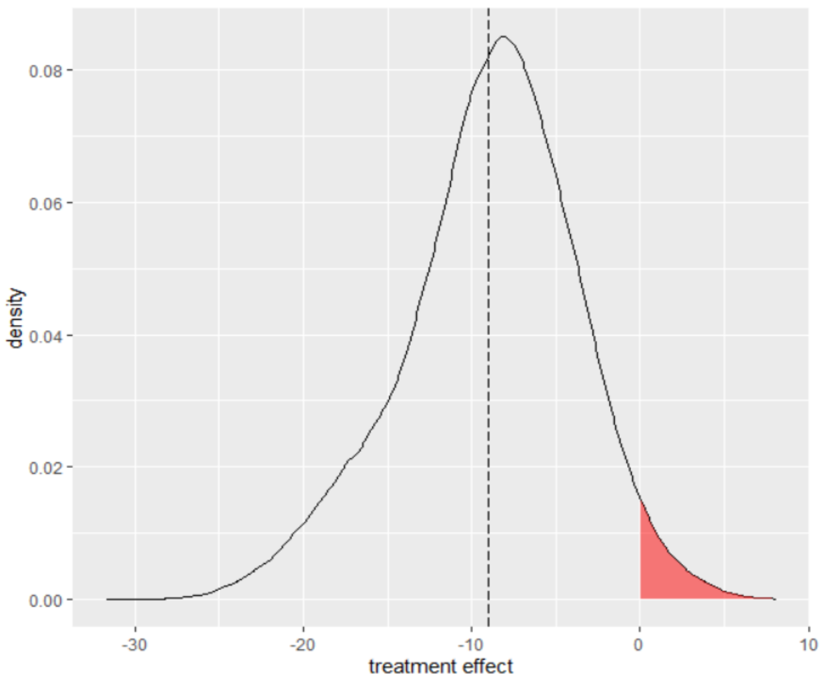
Dependent variable	N	Mean	SD.	Min.	Max.	Range	Test of heterogeneity	
							β^C	β^D
Log of cash-to-net assets	158,429	-9.002	5.162	-32.871	8.427	41.298	1.040 (29.815***)	1.244 (19.700***)
Cash-to-assets	158,429	-0.668	0.416	-3.871	1.661	5.532	1.058 (24.851***)	1.305 (14.429***)

Note: This table reports the summary statistics of the firm-level effect of cost of carry on cash holdings measures (logarithm of cash-to-net assets ratio, and cash-to-assets ratio) using cluster-robust (by firms) causal forest for the full sample period. The results of the heterogeneity test based on the best linear predictor (BLP) are presented in the last two columns. The confounders set consists of ten covariates (firm size, market-to-book ratio, financial leverage, dividends, cash flow, cash flow volatility, R&D, net working capital, capital expenditures, acquisitions). The sample consists of 158,429 firm-year observations from 17,062 unique firms retrieved from Compustat over 1971-2019. Financial (SIC code 6000-6999) and utility firms (SIC codes 4900-4999) are excluded from the sample. To mitigate the influence of outliers, all variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix 4.1. *, ** and *** denote significance at 10%, 5%, and 1% respectively.

Figure 4.1 provides a graphical examination of the heterogeneity of the cost of carry impact on corporate money demand. This figure illustrates the density of firm-level estimation results for the log of cash-to-net assets ratio.[44] Non-negative effects are highlighted in red. The vertical dashed line denotes the average effect of the cost of carry, reported in Table 2 (-9.002). It is clear that the cost of carry effects are noticeably distributed in the positive and negative territories as well as around zero. The domain of the distribution of the cost of carry effect contains values from around -30 to 10. However, most of the effects are negative, which is in line with theoretical predictions. These heterogeneous effects confirm that positive, negative, or non-significant relationships between cost of carry and cash holdings are possible in practice.

[44] The figure conveys similar results based on the alternative cash measure (i.e., cash-to-assets ratio).

Figure 4.1 Distributional impacts of cost of carry



Note: This figure illustrates the distribution of the firm-level cost of carry effect estimated by the causal forest method for the full sample period (1971-2019) reported in Table 2, for logarithm of cash-to-net assets ratio as the dependent variable. Non-negative effects are highlighted in red. The vertical dashed line denotes the average treatment effect (-9.002).

Collectively, the results in this section suggest that there is no simple association between opportunity costs, measured by the cost of carry and money demand. The spectrum encompasses a mix of firms with positive, neutral (small effect around zero), or negative associations, owing to the heterogeneity in the cost of carry effect. The reported heterogeneity unveiled in our findings could explain the mixed results reported in prior studies on the empirical relation between cash holdings and opportunity cost measures (e.g., Azar et al., 2016; Gao et al., 2021).

4.5.2 Determinants of the heterogeneity

This section focuses on the determinants of the heterogeneity of the cost of carry effects. In other words, we uncover the potential factors that cause the effect of cost of carry on cash holdings to vary. To better understand the routes of heterogeneity and for the sake of robustness, we conduct three sets of analyses.

First, following Li et al. (2021), to identify which covariates are the most responsible for the variability in the cost of carry effect, we calculate the variable importance scores derived from the fitted causal forest.[45] The scores identify which features can split the data space

[45] Variable importance measure for feature *i* is the weighted average of the number of times that the sample split is done based on that feature at each depth in the forest (Tibshirani et al., 2021).

such that the resulting groups are as different from each other as possible. The higher the score, the better the corresponding variable is in predicting treatment heterogeneity (Sylvia et al., 2021).

Column (1) of Table 4.3 presents the importance scores of firm characteristics. Among the ten variables used in the construction of the tree, firm size alone accounts for approximately 50% of splits, suggesting that firm size is by far the main source of the treatment effect heterogeneity. Net working capital and cash flow volatility are in second and third place, with importance scores of 16.6% and 14.3%, respectively. Dividends and acquisition expenditures, with scores of less than 1%, contribute the least to creating heterogeneity.

Second, we compare the average of firm characteristics across quantiles of the estimated effects of the cost of carry. Some online sources on the application of the causal forest method raise concerns that importance scores may not be able to identify all determinants of heterogeneity.[46] For this reason, some researchers propose to investigate the mean of variables across n-tiles of treatment effects (e.g., Davis and Heller, 2020).

Columns (2)-(6) of Table 3 compare the average of each firm characteristic across quintiles for the cost of carry effect estimated by the causal forest method. Standard deviations are reported in parentheses. The first (fifth) quintile Q1 (Q5) corresponds to the lowest (highest) effect of the cost of carry on cash holdings. According to the transactions cost model, the opportunity cost proxy has a negative effect on cash holdings. Thus, we consider firms in quintile Q1 (Q5) as the most (least) responsive firms to cost of carry changes. The Student's *t* statistic that tests the mean difference between the first and fifth quintiles are reported in the last column (Column (7)).

The largest difference between Q1 and Q5, in absolute value, is associated with firm size, which is highly statistically significant (t=139.020, Sig<0.01). This finding indicates that firm size is the main source of heterogeneity, which is consistent with our results based on the importance score analysis. Again, net working capital is identified as the second most important determinant responsible for the heterogeneity effect (t=96.375, Sig.<0.01). We also find that cash flow volatility (the third factor responsible for the heterogeneity based on importance scores) is replaced by financial leverage (t=73.469, Sig.<0.01).

By comparing the average of each firm characteristic across quintiles of estimated effects of cost of carry, we can also detect the coordinates of subgroups of firms with high or low

[46] For example, see https://gsbdbi.github.io/ml_tutorial/hte_tutorial/hte_tutorial.html

treatment effects. The averages among quintiles reveal that firms whose cash is more affected by the cost of carry (i.e., Q1) are larger (6.840 vs. 4.630) and are more leveraged firms (0.294 vs. 0.193) and have lower levels of net working capital (0.021 vs. 0.158) than those with lower sensitivity (i.e., Q5). Higher sensitivity of large firms' cash holdings to the cost of carry is consistent with the view that they are financially less constrained relative to their small counterparts (Almeida et al., 2004; Eskandari and Zamanian, 2022). Since large firms have the ability to raise funds from external capital markets to finance investment projects, they tend to follow procyclical waves in their cash management.

Table 4.3 Ranking of heterogeneity determinants

Variable	Importance score	Q1 (Lowest effect)	Q2	Q3	Q4	Q5 (Highest effect)	Mean difference (Q1 and Q5)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Firm size	0.495	6.840 (2.650)	4.980 (2.490)	4.470 (2.080)	4.430 (1.690)	4.630 (1.190)	139.020***
Growth opportunities	0.016	1.920 (1.360)	1.660 (1.330)	1.590 (1.300)	1.660 (1.330)	1.850 (1.560)	7.311***
Financial leverage	0.040	0.294 (0.159)	0.232 (0.175)	0.220 (0.186)	0.191 (0.190)	0.193 (0.186)	73.469***
Dividends	0.006	0.500 (0.500)	0.436 (0.496)	0.386 (0.487)	0.350 (0.477)	0.312 (0.463)	46.860***
Cash flow	0.028	0.020 (0.197)	0.021 (0.167)	0.027 (0.158)	0.032 (0.159)	0.019 (0.174)	1.032
Cash flow volatility	0.143	0.104 (0.054)	0.082 (0.054)	0.081 (0.051)	0.084 (0.048)	0.086 (0.047)	46.565***
R&D expenditure	0.091	0.123 (0.544)	0.093 (0.470)	0.086 (0.468)	0.103 (0.542)	0.204 (0.814)	14.725***
Net working capital	0.166	0.021 (0.151)	0.103 (0.183)	0.130 (0.193)	0.132 (0.202)	0.158 (0.210)	96.375***
Acquisitions	0.002	0.028 (0.065)	0.017 (0.051)	0.015 (0.049)	0.016 (0.049)	0.017 (0.048)	26.049***
Capital expenditure	0.014	0.060 (0.060)	0.066 (0.066)	0.068 (0.069)	0.068 (0.072)	0.062 (0.070)	2.500**
N	158,429	31,686	31,686	31,686	31,686	31,685	

Note: This table reports the importance score (Column (1)) and average (Columns (2)-(6)) of firm characteristics which are used in construction of the tree. The averages are calculated by quintiles (Q1-Q5) of cost of carry effect on the logarithm of cash-to-net assets ratio, estimated by the causal forest in Table 2. Standard deviations of firm characteristics are reported in parentheses. The absolute values of the Student's *t* statistic to test the mean difference between the first and fifth quintiles are reported in the last column. The sample consists of 158,429 firm-year observations from 17,062 unique firms retrieved from Compustat over 1971-2019. Financial (SIC code 6000-6999) and utility firms (SIC codes 4900-4999) are excluded from the sample. To mitigate the influence of outliers, all variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix 4.1. *, **, and *** denote significance at 10%, 5%, and 1% respectively.

Third, following Athey and Wager (2019), we conduct the best linear projection analysis of Semenova and Chernozhukov (2021) as a formal test to assess the heterogeneity along the identified important features in the forest. According to their importance scores and *t* statistics, reported in Table 3, firm size, net working capital, cash flow volatility, and financial leverage are the major factors creating the heterogeneity. Thus, we run the best linear projection analysis using these four variables.

Table 4.4 presents the results of the best linear projection analysis. The obtained results confirm that all identified determinants (i.e., firm size, net working capital, cash flow volatility, and financial leverage) have statistically significant roles in explaining the heterogenous effect of the cost of carry on cash holdings (Sig.<0.01).

Table 4.4 Best linear projection of cost of carry effect

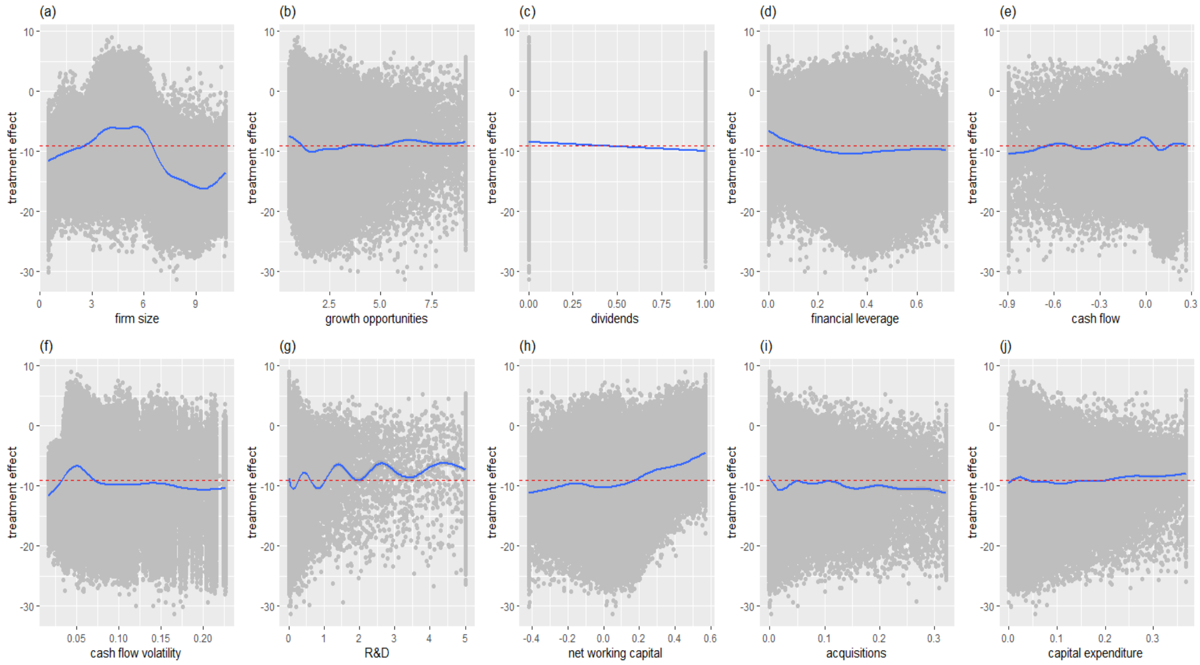
Variable	Estimate	t-statistics	Sig.
Intercept	-3.051	-2.649	0.008
Firm size	-0.572	-3.667	0.000
Net working capital	4.839	2.782	0.005
Cash flow volatility	-31.406	-4.052	0.000
Financial leverage	-7.060	-4.040	0.000

Note: This table reports the results of the best linear projection of the cost of carry effect using the four most important variables (i.e., firm size, net working capital, cash flow volatility, and financial leverage) identified in Table 3. To mitigate the influence of outliers, all variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix 4.1.

In Table 4.3, we can observe which groups of firms are sensitive or insensitive to the cost of carry. However, we may lose an important part of picture due to the grouping of observations within quantiles. To discover hard-to-observe patterns in the data, we follow Gulen et al. (2020) and examine the scatter plot of causal forest-based effects against firm characteristics. Figure 4.2 plots firm-level effects of the cost of carry on the logarithm of cash-to-net assets ratio against ten covariates. The horizontal dashed line denotes the average treatment effect (-9.002). We also add smooth curves using the nonparametric generalized additive model (GAM) to facilitate the identification of patterns.

Figure 2(a) indicates that firm size has a non-monotonic effect on the sensitivity of cash to the cost of carry. Starting from the left tail of the firm size distribution (small firms), the effect of the cost of carry on cash decreases (in absolute value) from below -10 to about -5 with firm size; it then increases to below -15 in the right tail of firm size. We would not have been able to identify this pattern using a traditional approach if we did not have a clear picture of the functional forms of the inter-relation among firm size, cash holdings, and cost of carry. The observed nonlinearity in Figure 2(a) can complement the results of Eskandari and Zamanian (2022). They rely on parametric models and did not find a non-linear effect of firm size on the cash-cost of carry relationship.[47] Regarding net working capital, as the second most important determinant of the heterogeneity, the GAM smooth curve (Figure 2(h)) suggests that firms with lower levels of net working capital are associated with stronger negative effects of cost of carry on cash holdings.[48] For variables which are not identified as determinants of the heterogeneity in the analysis as discussed above (i.e. R&D expenditure, cash flow, growth opportunities, capital expenditure, dividends, and acquisitions), the smooth curves largely remain around the reference line (average treatment effect).[49]

Figure 4.2 Cost of carry effect against firm characteristics



[47] We stress that, consistent with Eskandari and Zamanian (2022), demand for cash in large firms is more responsive to the cost of carry changes in comparison to small ones. This is because the smooth curve is totally below the reference line in the second half of the firm size distribution, while in the first half of the distribution some part of the curve is located on the above of the line.

[48] As a robustness check for the patterns detected by the GAM smooth curve, we produce partial dependence plots (PDPs) for the cost of carry effect on cash holdings with respect to firm size and net working capital, as the first and second important determinants of the heterogeneity, in Appendix 4.2. The PDP, as a useful tool for interpreting the results from black-box machine learning models, shows how a specific variable impacts the treatment effect after controlling the effect of other variables (the marginal effect), in a visual way (Zhao and Hastie, 2021). To draw the PDP, we predict the cost of carry effects on cash holdings by changing the variable on the *x*-axis on its quintiles, while keeping all the other covariates fixed at their medians. The results support our main findings based on the GAM. It would also be interesting to investigate the interaction effect of firm size and net working capital on the cost of carry impact. We produce a two-dimensional PDP of cost of carry effect on cash balances by deciles of firm size and net working capital in Appendix 4.3. The results show that cash holdings in large firms with low net working capital are the most sensitive to cost of carry, which is consistent with the patterns detected by GAM.

[49] It seems that there exists large variability in the scatter plot of R&D expenditures. Unreported results from the best linear projection analysis confirm that the effect of R&D on the heterogeneity is not statistically significant. This is also consistent with the results reported in Table 3, where we find no evidence to support the influence of R&D on the heterogeneity.

Note: This figure plots the firm-level cost of carry effect, estimated by the causal forest method in Table 2 for the logarithm of cash-to-net assets ratio, against firm characteristics. The horizontal dashed line denotes the average treatment effect (-9.002). The smooth line using a generalized additive model (GAM) is added to detect how cost of carry effect varies with covariates.

Conclusively, results in this section indicate that firm size, net working capital, cash flow volatility, and financial leverage are the most important features responsible for the heterogeneity of the cost of carry impact on cash holdings. Among these, firm size has a non-monotonic effect on the cash-cost of carry elasticity. Finally, there is little evidence to support the role of R&D expenditure, cash flow, growth opportunities, capital expenditure, dividends, and acquisitions on creating heterogeneous impacts of the cost of carry.

4.6 Additional Analysis

4.6.1 Cross-sectional heterogeneity

Due to the dynamic nature of corporate cash holdings, many researchers try to investigate the evolution of cash management over time (e.g., Bates et al., 2009; Graham and Leary, 2018). In this section, to assess how the heterogeneity in the cost of carry effect evolves over time, we utilize the causal forest method on the cash-cost of carry relation within five-decade subsamples (1970s, 1980s, 1990s, 2000s, and 2010s), separately.

Panel A of Table 4.5 (Columns (1)-(7)) reports the summary statistics of the estimated effects. Three main findings are worth noting from these results.[50] First, on average, there is a stable negative relation between the cost of carry and cash holdings over all five decades. For example, the sensitivity of cash to cost of carry is -13.949, on average, in the first decade of our sample (i.e., the 1970s). This sensitivity also carries a negative sign (-24.960) in the last decade (i.e., the 2010s).

Second, there is an increasing heterogeneity in the cost of carry effect on cash holdings over time, as reported by the standard deviation and the range index. For example, the standard deviation of the firm-level cost of carry effects rises dramatically from 2.572 during the 1970s to 19.855 during the 2010s. That is an eight-fold increase.

Third, and most importantly, the positive values for the estimated effects are *only* visible in recent decades. The maximum values of the cost of carry effect on corporate cash in the 1970s and 1980s are negative, -5.177 and -1.197, respectively, indicating that all firms manage their cash holdings in a reverse direction to the cost of carry in the earlier decades.

[50] The obtained results based on the alternative cash measure (i.e., cash-to-assets ratio) are very similar; see Appendix 4.4.

By contrast, the maximum values for subsequent decades are positive (0.857, 6.130, and 55.870 for the 1990s, 2000s, and 2010s, respectively), suggesting that some firms experience a positive relation between their cash balances and cost of carry changes. The percentage of non-negative effects, presented in Column (7), confirm that it is more likely to observe positive effects in recent decades than in the past (for example, 9.818% in the 2010s vs. 0.000 in the 1970s). This result suggests that the breaching of the transaction model's postulation starts becoming more relevant after the 1990s.

The last two columns of Table 5 present the best linear predictor test results to statistically assess the identified heterogeneity in the cost of carry effect on cash holdings. We find that the causal forest method adequately captures the heterogeneity in the effect of the cost of carry for five decades (Sig.<0.01). Particularly, this is also true for early decades (i.e., the 1970s and 1980s) with completely negative effects. In other words, although firms perfectly followed the transaction model in their cash management (negative relation between cash holdings and opportunity cost) in these two decades, there is significant heterogeneity in the effect of the cost of carry on cash holdings at firm level, in terms of magnitude.

To compare the distributional impact of the cost of carry, two-sample Kolmogorov-Smirnov (KS) test results are reported in Panel B of Table 5. These results indicate that, first, the empirical cumulative distribution function (ECDF) of the 1970s, for example, is statistically different from the ECDFs of subsequent decades (Sig.<0.01). Second, the distance between ECDFs increases over time (the KS test statistic is based on the distance between ECDFs). For example, the distance between ECDFs of the 1980s and 1990s equals 0.447, while this distance grows to 0.524 between ECDFs of the 1980s and 2010s. These findings confirm that firms' cash management in response to cost of carry changes has its own distributional characteristics (time dependencies of opportunity cost effect on liquidity) in each decade and is performed differently in recent years as compared to the past.

Table 4.5 Cross-sectional heterogeneity in the cost of carry effect

Panel A: *Summary statistics*

Decade	N	Mean	SD.	Min.	Max.	Range	Non-negative effects (%)	Test of heterogeneity β^C	Test of heterogeneity β^D
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1970s	22,652	-13.949	2.572	-26.566	-5.177	21.389	0.000	1.018 (28.306***)	1.277 (6.673***)
1980s	24,149	-12.323	4.132	-38.101	-1.197	36.903	0.000	1.017 (24.672***)	1.268 (9.467***)
1990s	39,586	-17.426	5.610	-46.109	0.857	46.967	0.003	1.006	0.970 (7.073***)

								(21.807***)	
2000s	39,510	-19.840	7.950	-53.380	6.130	59.506	0.043	1.061 (22.065***)	1.227 (10.229***)
2010s	32,532	-24.960	19.855	-111.490	55.870	167.355	9.818	1.222 (10.185***)	1.457 (9.160***)

Panel B*: Kolmogorov-Smirnov test*

	1970s	1980s	1990s	2000s
1980s	0.309***			
1990s	0.425***	0.447***		
2000s	0.505***	0.479***	0.194***	
2010s	0.564***	0.524***	0.383***	0.245***

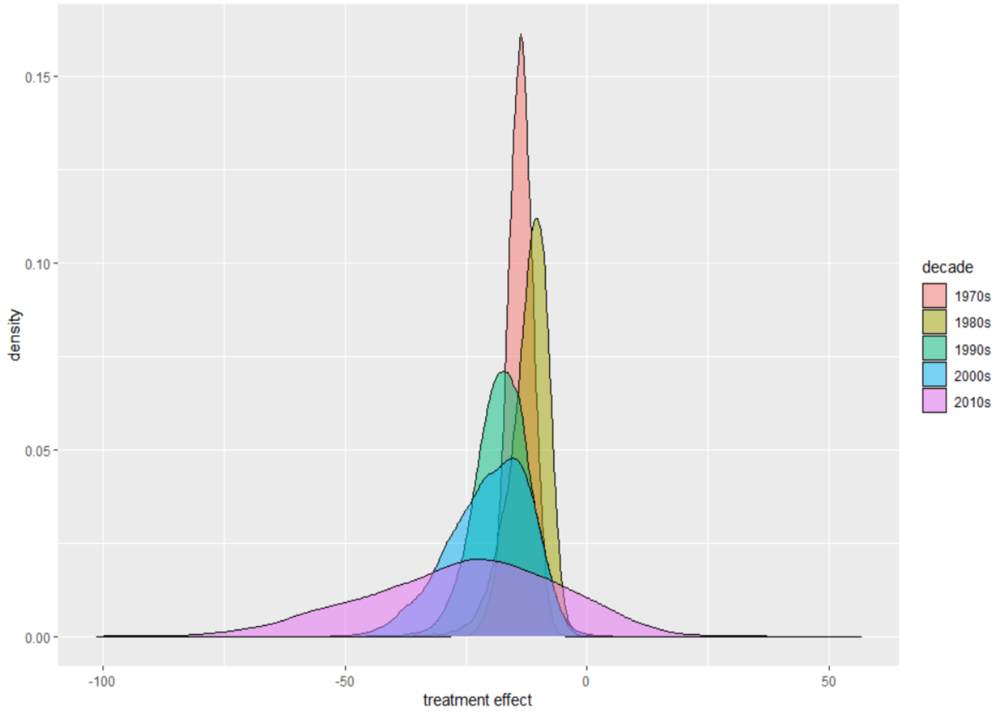
Note: This table reports the summary statistics of the firm-level effect of cost of carry on cash holdings using cluster-robust (by firms) causal forest for five decades (1970s, 1980, 1990s, 2000s, and 2010s) in Panel A. The results of the heterogeneity test based on the best linear predictor (BLP) is presented in the last two columns. Two-sample Kolmogorov-Smirnov (KS) test results are reported in Panel B. The null hypothesis in the KS test is that the distributional impacts of cost of carry are identical in each pair of decades. The dependent variable is log of cash-to-net assets ratio. The confounders set consists of ten covariates (firm size, market-to-book ratio, financial leverage, dividends, cash flow, cash flow volatility, R&D, new working capital, capital expenditures, and acquisitions). The sample consists of 158,429 firm-year observations from 17,062 unique firms retrieved from Compustat over 1971-2019. Financial (SIC code 6000-6999) and utility firms (SIC codes 4900-4999) are excluded from the sample. To mitigate the influence of outliers, all variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix 4.1. *, **, and *** denote significance at 10%, 5%, and 1% respectively.

Figure 4.3 graphically depicts and compares the heterogeneous effect of the cost of carry on cash holdings across all five decades. The domain of the estimated effects has grown wider across decades,[51] with non-significant and positive values which are more likely to be observed in recent decades. This is consistent with the numerical results reported in Table 5.[52]

[51] To investigate whether there exists increasing heterogeneity prior to the 1980s, we conduct the causal forest estimation process separately for the first and second halves of the 1970s and compare the results with those of the 1980s. The results are reported in Appendix 4.5. The dispersion metrics (standard deviation, interquartile range, and range index) suggest that the heterogeneity diminished in the second half of the 1970s relative to the first half. This contrasts with the increasing heterogeneity in the second half of the 1980s as compared to the first.

[52] As a robustness check, we replace the cost of carry with the raw interest rate (nominal 3-month T-bill rate) and repeat the cross-sectional analysis. Due to the potential endogeneity problem between raw interest rate and cash holdings, we follow Gao et al. (2021) and instrument the raw interest rate with monetary policy shocks from Nakamura and Steinsson (2018) and run an instrumental causal forest. Distributional impacts of the raw interest rate by five-year windows, reported in Appendix 4.6, are largely similar to the results depicted in Figure 2, with two notable results. First, heterogeneity in the interest rate effect becomes more pronounced over the years. Second, the positive effects are more likely to be observed in recent years.

Figure 4.3 Heterogeneous effect of cost of carry by decades



Note: This figure compares the distribution of firm-level cost of carry effect estimated by the causal forest method, reported in Table 5, for five decades (1970s, 1980, 1990s, 2000s, and 2010s).

Conclusively, we document that the heterogeneity in the effect of cost of carry on corporate liquidity has increased from the 1980s, and the positive effects started to appear from the 1990s. These two findings can be explained by financial reforms triggered by high inflation rates in the 1980s and financial innovations in the 1990s, respectively.[53] First, the increasing heterogeneity in the effect of cost of carry on corporate liquidity coincides with the gradual lifting of Regulation Q in the late 1970s and early 1980s. Given the constraints this regulation imposed on legal deposit rate ceilings, firms were forced to follow the transaction model predictions and hold most of their liquid assets in the form of non-interest-bearing assets, such as cash, checks, demand deposits, etc. (Azar et al., 2016; Cardella et al., 2021). Because of that, we observe a *narrow* distribution of the cost of carry effect on cash holdings in the 1970s, indicating that firms' cash reserves reacted to opportunity costs with a very similar pattern. After lifting the interest rate ceilings, corporate treasurers were able to manage their resources with more freedom of action and respond to the interest rate shocks by parking their cash reserves in interest-bearing assets, such as commercial paper, marketable securities, etc., which are alternatives to the traditional forms of liquid asset (Azar et al., 2016). As a result, we now observe *broader* distributions for the cost of carry

[53] Indeed, it is well documented that changes in financial regulations and financial innovations are the most important factors that may shift the money demand function (Berentsen et al., 2018). These two factors are incorporated in recent extensions of the Baumol-Tobin model to describe the money demand instability (e.g., Benati et al., 2021, Lucas and Nicolini, 2015).

effects with more heterogeneity in the subsequent decades relative to the 1970s, suggesting that firms may not necessarily manage their liquidity consistent with theoretical predictions in recent years. This is consistent with Lucas and Nicolini's (2015) findings and the money demand instability literature. Referring to the early 1980s as a 'hectic period in terms of regulatory changes', they find that lifting Regulation Q weakened the long-lasting equilibrium between interest rates and money demand, which has never revived.

Second, the introduction of retail deposit sweep programs, as a major financial innovation in the first half of the 1990s, exacerbated the observed heterogeneity in the cost of carry effect, i.e., observing positive effects for the first time in our sample period. The changes made in payment methods under the influence of this technology substantially decreased the cost and time required to convert less liquid assets (e.g., government bonds) into currency for transaction purposes (Azar et al., 2016; Teles and Zhou, 2005). This technological progress gave corporations increasing control over their cash reserves; as a result, some firms started to manage their liquidity outside the framework set by theoretical models. This argument is in line with studies in monetary economics literature. For example, according to Berentsen et al. (2015), the empirical relation between money demand and interest rate began to change at the beginning of the 1990s due to the introduction of sweep technology.[54]

Following the empirical causal effect approach in our main analysis, we repeat quantify and compare the factor contribution in the cost of carry effect heterogeneity by decade. Panel A of Table 4.6 presents the variable importance scores and the corresponding ranks of the ten observable characteristics across five decades. Several notable findings can be drawn from these results. First, capital expenditures, which is the variable that most contributed to creating heterogeneity in the 1970s (with importance score 0.227 and rank 1), when Regulation Q was not completely repealed, gradually lost its importance over decades (rank 3, 4, and 6 in the 1980s, 1990s, and 2000s, respectively). Nevertheless, it regains higher importance in the last decade (i.e., rank 4 in the 2010s). Second, while in the 1970s, net working capital was ranked eighth, it was among the top three drivers of heterogeneity over recent decades. Finally, firm size, which is the most important driver of heterogeneity in the full sample, achieved its importance only in recent decades (rank 1 and 2 in the 1990s and 2010s, respectively).

[54] At the micro level, Alvarez and Lippi (2009) document that cash management patterns for households are inconsistent with Baumol-Tobin's transactions model in the presence of financial innovation, which makes cash withdrawal at low cost possible.

Overall, the obtained results indicate that the ranking of covariates in early decades does not concord with rankings in subsequent decades. This is supported by Kendall's coefficients test among the ten possible pairwise comparisons reported in Panel B of Table 6. For example, there are no significant concordance coefficients between the 1970s and any other decade, indicating that there is no agreement between 1970s' ranks and other sets of ranks. By contrast, the concordance coefficients generally increase after the 1970s and 1980s such that some of them are statistically significant at 10%, e.g., 0.818 between the rank set of the 1990s and 2010s.

Table 4.6 Determinants of heterogeneity by decades

Panel A: *Variable importance scores*										
	1970s		1980s		1990s		2000s		2010s	
variable	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
Firm size	0.121	4	0.038	7	0.334	1	0.083	4	0.119	2
Growth opportunities	0.156	2	0.027	8	0.054	5	0.130	2	0.051	7
Financial leverage	0.072	7	0.046	6	0.198	2	0.124	3	0.065	5
Dividends	0.005	9	0.003	9	0.005	10	0.002	10	0.017	9
Cash flow	0.127	3	0.121	4	0.048	6	0.036	7	0.025	8
Cash flow volatility	0.114	5	0.378	1	0.041	7	0.498	1	0.483	1
R&D	0.103	6	0.074	5	0.022	8	0.015	8	0.062	6
Net working capital	0.071	8	0.162	2	0.150	3	0.058	5	0.091	3
Acquisitions	0.004	10	0.002	10	0.011	9	0.003	9	0.010	10
Capital expenditure	0.227	1	0.148	3	0.136	4	0.051	6	0.075	4
No. observation	22,652		24,149		39,586		39,510		32,532	

Panel B: *Kendall's concordance coefficients*				
	1970s	1980s	1990s	2000s
1980s	0.685			
1990s	0.709	0.655		
2000s	0.733	0.721	0.806	
2010s	0.673	0.861*	0.818*	0.855*

Note: This table compares the importance of covariates in the trees grown by causal forest, estimated in Table 5, among five decades (1970s, 1980, 1990s, 2000s, and 2010s) in Panel A. Kendall's coefficient, as a measure of concordance between each pair of ranks, is reported in Panel B. The null hypothesis of Kendall's coefficient test is that there is no agreement between ranks. To mitigate the influence of outliers, all variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix 4.1. *, **, and *** denote significance at 10%, 5%, and 1% respectively.

4.6.2 The heterogeneity around financial crisis

The Global Financial Crisis of 2008 dramatically changed the process of liquidity management among US firms, as it influenced the supply of credit (e.g., Ivashina and

Scharfstein, 2010) and created a shift in the interest rate dynamics. To boost the US economy, the Fed pursued a policy of reducing interest rates approaching the zero lower bound (ZLB) limit after the crisis (Altavilla et al., 2022). Particularly, the 3-month T-bill rate has been less than 2% for over a decade (Gao et al., 2021).

In this section, we examine the heterogeneous effect of cost of carry on cash holdings around the 2008 financial crisis. Unique features of the interest rate dynamic before and after this financial turbulence create an ideal natural experimental situation for assessing how the sensitivity of cash to cost of carry changes under the shock of an exogeneous factor.

Table 4.7 presents the causal forest estimation results within five-year windows around the 2008 financial crisis; that is, for the periods 2003-2007 and 2008-2012. As expected, the cost of carry has an average negative effect on cash holdings during both pre- (-23.917) and post-crisis (-41.790) periods. The heterogeneity in the cash-cost of carry relation in the post-crisis era is higher than the pre-crisis one, both in terms of range index and standard deviation. The standard deviation and range of effects for the pre-crisis period are 8.109 and 59.724, respectively, in contrast to 27.883 and 190.740 for the post-crisis period. According to the best linear predictor test results, in the last two columns, causal forest adequately captures the heterogeneity before and after the crisis (Sig.<0.01). Finally, a two-sample Kolmogorov-Smirnov test indicates that the difference between the distributional impact of cost of carry in the pre and post-crisis periods is statistically significant (KS=0.462, Sig.<0.01).

Table 4.7 Heterogeneous effect of cost of carry around financial crisis

Period	N	Mean	SD.	Min.	Max.	Range	Test of heterogeneity	
							β^C	β^D
Pre-crisis (2003-2007)	19,644	-23.917	8.109	-58.561	1.163	59.724	1.030 (15.193***)	0.932 (4.903***)
Post-crisis (2008-2012)	17,608	-41.790	27.883	-155.660	35.080	190.740	1.137 (12.301***)	1.310 (8.479***)
Two-sample Kolmogorov-Smirnov test					0.462***			

Note: This table compares the summary statistics of the firm-level effect of cost of carry on cash holdings between five-year windows around the 2008 global financial crisis (2003-2007 vs. 2008-2012). The results of the heterogeneity test based on the best linear predictor (BLP) are presented in the last two columns. The two-sample Kolmogorov-Smirnov (KS) test result is reported at the bottom line. The null hypothesis in the KS test is that the distributional impact of cost of carry is identical pre and post crisis. The dependent variable is logarithm of cash-to-net assets ratio. The confounders set consists of ten covariates (firm size, market-to-book ratio, financial leverage, dividends, cash flow, cash flow volatility, R&D, net working capital, capital expenditures, and acquisitions). The sample consists of 158,429 firm-year observations from 17,062 unique firms retrieved from Compustat over 1971-2019. Financial (SIC code 6000-6999) and utility firms (SIC codes 4900-4999) are excluded from the sample. To mitigate the influence of outliers, all variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix 4.1. *, **, and *** denote significance at 10%, 5%, and 1% respectively.

To provide a better comparison between the distributional impacts of cost of carry on cash holdings pre and post 2008 global financial crisis, we depict the firm-level treatment effects generated from the causal forest in Appendix 4.7. The concentrated distribution around the average negative effect (-23.917) before the crisis becomes a scattered distribution with well-spread effects over the positive and negative values after the crisis. This implies that the financial crisis has deeply affected money markets and thus distorted the hypothesized negative relation between cash holdings and opportunity cost proxy.

Variable importance scores are presented in Table 4.8 to identify covariates responsible for the heterogeneity in the pre and post-crisis periods. We find that two of the top three covariates in the tree grown by causal forest are the same pre and post crisis. Cash flow volatility and growth opportunities are identified as the first and second most important factors for cost of carry heterogenous effects in the pre-crisis period, with importance scores of 28.7% and 17.4%, respectively. These variables are the first and third most influential determinants of heterogeneity in the post-crisis era, with importance scores of 56.6% and 10.2%, respectively. Kendall's coefficient confirms that there is a statistically significant concordance (0.824, Sig.<0.1) between two sets of covariates' rank in the pre- and post-crisis periods.

These findings indicate that although under the 2008 financial crisis the elasticity of cash to cost of carry dramatically changed, the importance rank of firm-specific drivers behind this heterogeneity in the post-crisis period is largely similar to the pre-crisis period.

Table 4.8 Determinants of heterogeneity around financial crisis

Variable	Pre-crisis (2003-2007)		Post-crisis (2008-2012)	
	Score	Rank	Score	Rank
Firm size	0.101	5	0.032	7
Growth opportunities	0.174	2	0.102	3
Financial leverage	0.082	6	0.104	2
Dividends	0.006	9	0.003	10
Cash flow	0.062	7	0.040	6
Cash flow volatility	0.287	1	0.566	1
R&D	0.021	8	0.047	5
Net working capital	0.123	4	0.065	4

Acquisitions	0.005	10	0.010	9
Capital expenditure	0.138	3	0.030	8
No. observation	19,644		17,608	
Kendall's concordance coefficient		0.824*		

Note: This table compares the importance of covariates in the trees grown by causal forest, estimated in Table 7, between five-year windows around the 2008 global financial crisis (2003-2007 vs. 2008-2012). Kendall's coefficient, as a measure of concordance between two sets of ranks, is also reported at the bottom line. The null hypothesis of Kendall's coefficient test is that there is no agreement between two sets of ranks. To mitigate the influence of outliers, all variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix 4.1. *, **, and *** denote significance at 10%, 5%, and 1% respectively.

4.6.3 The heterogeneity by industry

Despite extensive studies on the role of industry classification in cash management (Azar et al., 2016; Eskandari and Zamanian, 2022), there is still little evidence on the cash-opportunity cost sensitivity across sectors. In this section, we extend our knowledge of the heterogeneity by comparing the cash holdings elasticity to the cost of carry among different sectors. Given the different nature of business environments, it is expected that firms that hold a large amount of non-interest-bearing assets should react to changes in the interest rate differently than those operating in industries that require fewer non-interest-bearing assets.

We follow Azar et al. (2016) and define four industry groups based on two-digit SIC codes: manufacturing (SIC code 20–39), services (SIC code 70–89), retail trade (SIC code 52–59), and other industries. In our sample, manufacturing corporations have the largest representation (53.4%), followed by services (16.2%), and retail trade (8.3%). Other industries comprise 22.1% of the sample. We estimate firm-level effects of cost of carry on cash holdings using the causal forest method to determine the difference in cash management in response to opportunity cost changes among different industries.

Panel A of Table 4.9 presents the summary statistics of cost of carry effect on cash holdings for four industries. In all sectors, an average negative effect (-9.376, -11.842, -7.059, and -9.919 for manufacturing, services, retail trade, and other industries, respectively) is obtained, as expected. According to dispersion metrics, retail trade firms are the most homogeneous sector in terms of the elasticity of cash to cost of carry. The standard deviation and range index for the retail industry are 3.296 and 26.109, respectively, and are the smallest values among all sectors. According to Friedman (1959), retailers hold cash for immediate transactions with customers and suppliers and should respond quickly to changes in the interest rate (Azar et al., 2016). Thus, firms operating in the retail trade industry tend to follow more aligned practices in their cash management, in comparison to other industries. As a result, we observe a more homogeneous cost of carry effect in the retail trade industry.

This finding cannot be easily detected by conventional regression analysis. The BLP test results, reported in the last two columns of Table 9, indicate that there exists a significant heterogeneity in all sectors, suggesting important industrial impact on the cash-cost of carry relation.

Panel B of Table 4.9 shows the two-sample Kolmogorov-Smirnov (KS) test statistics. The null hypothesis in the KS test is that the distributional impacts of the cost of carry are identical in each pair of industries. We find that the distribution of the cost of carry effect on cash holdings is statistically different between industries in all six possible comparisons (Sig.<0.01). This finding suggests that, given the different business environment and cash flow shocks, firms operating in a specific industry manage their liquidity uniquely from other industries in response to opportunity cost fluctuations.

Table 4.9 Heterogeneous effect of cost of carry by industry

Panel A*: Summary statistics*

Industry	N	Mean	SD.	Min.	Max.	Range	Test of heterogeneity	
							β^C	β^D
Manufacturing	84,613	-9.376	5.947	-34.275	12.537	46.811	1.051 (22.482***)	1.236 (15.997***)
Services	25,722	-11.842	4.486	-35.703	1.637	37.339	1.062 (14.454***)	1.195 (6.269***)
Retail trade	13,083	-7.059	3.296	-22.145	3.964	26.109	1.022 (8.031***)	0.914 (3.855***)
Other	35,011	-9.919	5.944	-32.057	5.770	37.827	1.009 (13.568***)	1.138 (8.598***)

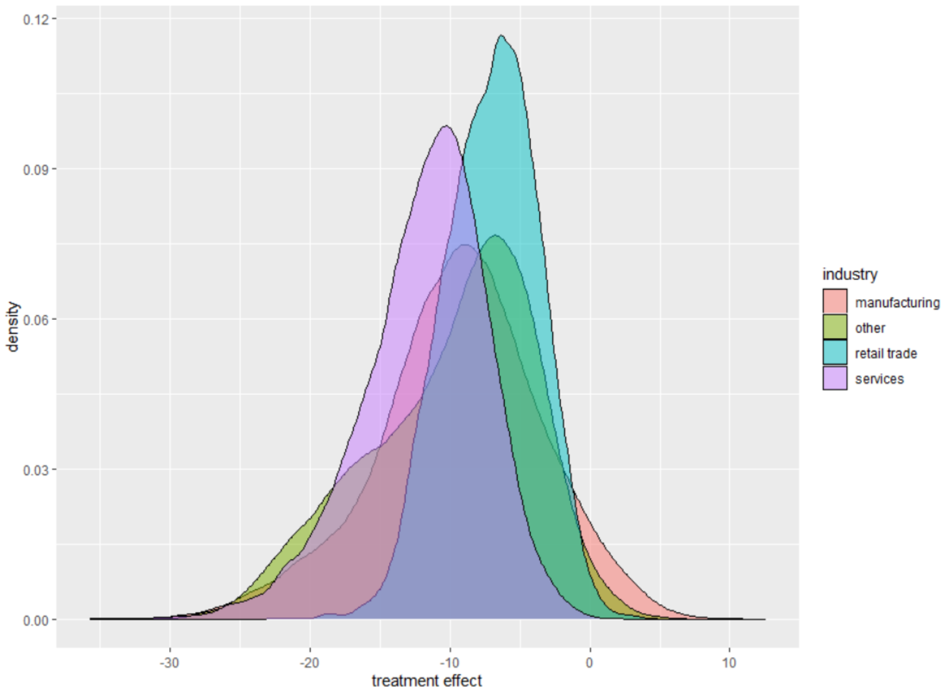
Panel B*: Kolmogorov-Smirnov test*

	Manufacturing	Services	Retail trade
Services	0.218***		
Retail trade	0.235***	0.421***	
Other	0.064***	0.238***	0.259***

Note: This table reports the summary statistics of the firm-level effect of cost of carry on cash holdings by industry in Panel A. Four industry sections are considered based on two-digit SIC codes: manufacturing (SIC code 20–39), services (SIC code 70–89), retail trade (SIC code 52–59), and other industries. Estimated effects are based on the cluster-robust (by firms) causal forest method. The results of the heterogeneity test based on the best linear predictor (BLP) are reported in the last two columns. Two-sample Kolmogorov-Smirnov (KS) test results are reported in Panel B. The null hypothesis in the KS test is that the distributional impacts of cost of carry are identical in each pair of industries. The dependent variable is logarithm of cash-to-net assets ratio. The confounders set consists of ten covariates (firm size, market-to-book ratio, financial leverage, dividend, cash flow, cash flow volatility, R&D, net working capital, capital expenditures, and acquisitions). The sample consists of 158,429 firm-year observations from 17,062 unique firms retrieved from Compustat over 1971-2019. Financial (SIC code 6000-6999) and utility firms (SIC codes 4900-4999) are excluded from the sample. To mitigate the influence of outliers, all variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix 4.1. *, **, and *** denote significance at 10%, 5%, and 1% respectively.

Figure 4.4 provides a visual comparison of the distributional impacts of the cost of carry on cash holdings among four industries. This figure also suggests a more homogeneous treatment effect in the retail trade sector. The density of this sector is narrower than the densities of other industries. There is more kurtosis and more concentrated effects around the average effect (-7.059). After the retail industry, the services industry exhibits the most homogeneity. Two other sectors (i.e., manufacturing, and other industries) are similar in terms of the heterogeneous effects of the cost of carry on cash holdings (the densities of these two sectors are very similar to each other and different from others). This is consistent with KS test statistics reported in Panel B of Table 9 where the corresponding statistic is the smallest (0.064).

Figure 4.4 Distributional impacts of cost of carry by industry



Note: This figure compares the distribution of firm-level cost of carry effect estimated by the causal forest method for four sectors (manufacturing, services, retail trade, and other industries) reported in Table 9.

To assess the contribution of covariates in creating the heterogeneity across the different sectors, we investigate the importance scores of the ten observables, which are separately generated from the causal forests based on data from four industries. These scores, along with their corresponding ranks, are reported in Panel A of Table 10.[55] The variable importance scores reveal that firm size is among the top variables (the first (second) variable in manufacturing and other (services and retail trade) industries) influencing the relationship between opportunity cost measure and cash holdings across all industries. This finding

[55] Appendix 4.8 graphically compares the magnitude of the importance scores of covariates in the trees of four industry sections.

underscores the importance of scale economies in cash management, which is consistent with the transactions model (see, for example, Mulligan (1997) and Ysmailov (2021)). Acquisition expenditure is the covariate with the least contribution (rank 10 (9) in services and manufacturing (retail trade and other) industries) in creating the heterogeneous effect of cost of carry, which is consistent with our finding in the main analysis based on the full sample.

In Panel B of Table 4.10, the two largest concordance coefficients and the only significant ones at 10% are 0.927 and 0.897, corresponding to manufacturing-other and services-retail pairs, respectively. These coefficients indicate that the covariates responsible for the heterogeneity in the cash-cost of carry relation in the services (manufacturing) industry are very similar to the retail (other) industries. The weakest agreement is between services and firms operating in other industries, with a concordance coefficient of 0.642.

Table 4.10 Determinants of heterogeneity by industry

Panel A: *Variable importance scores*

Variable	Manufacturing		Services		Retail trade		Other	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank
Firm size	0.291	1	0.129	2	0.179	2	0.471	1
Growth opportunities	0.018	6	0.079	7	0.090	6	0.040	8
Financial leverage	0.121	5	0.088	5	0.095	4	0.067	4
Dividends	0.009	9	0.097	4	0.039	8	0.003	10
Cash flow	0.014	7	0.087	6	0.171	3	0.056	5
Cash flow volatility	0.139	4	0.289	1	0.252	1	0.048	7
R&D	0.169	3	0.031	9	0.001	10	0.109	3
Net working capital	0.225	2	0.118	3	0.092	5	0.151	2
Acquisitions	0.002	10	0.019	10	0.010	9	0.004	9
Capital expenditure	0.013	8	0.063	8	0.070	7	0.051	6
No. observation	84,613		25,722		13,083		35,011	

Panel B: *Kendall's concordance coefficients*

	Manufacturing	Services	Retail trade
Services	0.776		
Retail trade	0.733	0.897*	
Other	0.927*	0.642	0.673

Note: This table compares the importance of covariates in the trees grown by causal forest, estimated in Table 9, among industries in Panel A. Four industry sections are considered based on two-digit SIC codes: manufacturing (SIC code 20–39), services (SIC code 70–89), retail trade (SIC code 52–59), and other industries. Kendall's coefficients, as a measure of concordance between each pair of ranks, are reported in Panel B. The null hypothesis of Kendall’s coefficient test is that there is no agreement between ranks. To mitigate the influence of outliers, all variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix 4.1. *, **, and *** denote significance at 10%, 5%, and 1% respectively.

4.6.4 Accounting for omitted variables

Azar et al. (2016) introduce the cost of carry as a descriptor for the secular increase in cash holdings among US industrial firms, a phenomenon first proposed by Bates et al. (2009). In addition to the cost of carry, some other potential descriptors have been proposed in the literature (for a review, see Graham and Leary, 2018). Thus, there is a concern that our main results may be biased due to ignoring the effect of these variables on cash- the omitted variables bias.

To address this concern, we add some of the well-known factors to the ten basic confounders which are used in the main analysis. These new confounders are industrial diversification (Bakke and Gu, 2017), intangible assets (Falato et al., 2020), multinationality (Fernandes and Gonenc, 2016), tax costs of repatriating earnings (Foley et al., 2007), debt maturity (Harford et al., 2014), and tangible assets (Lei et al., 2018). We refer to a set of confounders including these new covariates as augmented confounders.

We utilize the causal forest to estimate firm-level effects of the cost of carry on cash holding measures (log of cash-to-net assets, and cash-to-assets) in the presence of augmented confounders. More precisely, the set of confounders which may affect the relationship between the cost of carry and cash consists of ten basic covariates (e.g., firm size, leverage, cash flow, etc.) plus six potential drivers of secular increase in cash as discussed above. Following Bates et al. (2009), the analysis starts from 1980, which is the beginning of cash increase among US firms.

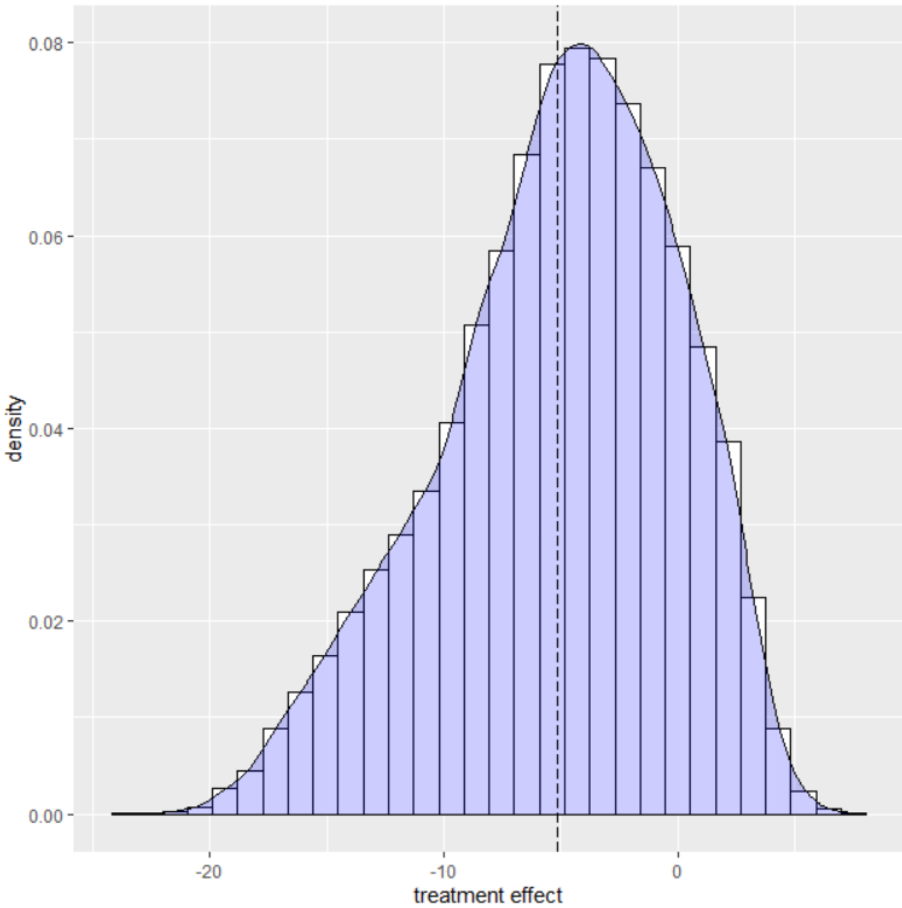
Table 4.11 presents the results. We find that after controlling for the effect of augmented confounders, there still exists a significant heterogeneity in the cost of carry effect, as the BLP test results reveal in the last two columns. To elaborate, although on average the cost of carry has a negative effect on both cash measures (-5.001 and -0.329 on log of cash-to-net assets and cash-to-assets, respectively) there is also evidence of a positive relation between the cost of carry and cash holdings (the largest values of estimated effects are positive) for both cash proxies. Figure 4.5 shows the heterogeneity of the cost of carry effect in the presence of augmented confounders. Overall, these results indicate that our main findings are not driven by omitted variable bias.

Table 4.11 Heterogeneous effect of cost of carry: Augmented confounders

Dependent variable	N	Mean	SD.	Min.	Max.	Range	Test of heterogeneity	
							β^C	β^D
Log of cash-to-net assets	71,132	-5.001	4.883	-22.926	7.530	30.456	1.100 (14.107***)	1.258 (16.461***)
Cash-to-assets	71,132	-0.329	0.307	-1.940	0.325	2.266	1.081 (12.363***)	1.234 (10.486***)

Note: This table reports the summary statistics of the firm-level effect of cost of carry on cash holdings measures (logarithm of cash-to-net assets ratio, and cash-to-assets ratio) using cluster-robust (by firms) causal forest for the period 1980-2019. The results of the heterogeneity test based on the best linear predictor (BLP) are presented in the last two columns. The confounders set consists of ten basic covariates plus six potential drivers of the cash increase proposed in the literature, including industrial diversification (Bakke and Gu, 2017), intangible assets (Falato et al., 2020), multinationality (Fernandes and Gonenc, 2016), tax costs of repatriating earnings (Foley et al., 2007), debt maturity (Harford et al., 2014), and tangible assets (Lei et al., 2018). The sample consists of 71,132 firm-year observations from 10,683 unique firms retrieved from Compustat. Financial (SIC code 6000-6999) and utility firms (SIC codes 4900-4999) are excluded from the sample. To mitigate the influence of outliers, all variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix 4.1. *, **, and *** denote significance at 10%, 5%, and 1% respectively.

Figure 4.5 Distributional impacts of cost of carry: Augmented confounders



Note: This figure illustrates the distribution of firm-level cost of carry effect estimated by the causal forest method for the period 1980-2019. The dependent variable is the logarithm of cash-to-net assets ratio. The vertical dashed line denotes the average treatment effect (-5.001).

4.7 Implications

Our takeaway from the identified heterogeneity in the effect of cost of carry are twofold. First, the impact of cost of carry on cash holdings is non-monotonic with respect to some of the firms' observable characteristics. In other words, firms nonlinearly differ in terms of their marginal benefit of holdings cash. Particularly, we document a hump-shaped effect of firm size on the relation between cost of carry and cash holdings. This finding is important for academics who needs to consider this nonlinearity in their analysis. Eskandari and Zamanian (2022) compare the empirical relation between cost of carry and cash holdings between constrained and unconstrained firms. They use different proxies to define these two groups including firm size. Utilizing dummy variable on firm size is implicitly based on the assumption of 'flat prior' meaning that the sensitivity of cash to cost of carry linearly changes with firm size (Azar et al., 2016), which contrasts with our findings. Generally, the empirical relation between opportunity cost measures, such as interest rates and cost of carry, across different groups of firms is an under-studied topic in literature mostly due to low statistical power (e.g., Gao et al., 2021). Our hope is that these findings help to establish a new standard for testing future hypotheses about the relationship between interest rates and money demand among different groups of firms.

Second, the heterogeneous impact of cost of carry on corporate cash holdings is of great importance for policymakers. Our results show that liquidity management in large firms, for example, is more responsive to changes in cost of carry. In other words, consistent with the heterogeneous agent model (e.g., Ottonello and Winberry, 2020), firms are not homogeneous in response to changes in monetary policy. As a result, individualized support programs should be designed to alleviate the adverse effects of tightening episodes, like increasing the unemployment rate and reducing the economic efficiency, when holding liquid assets is so expensive for firms and they face with liquidity shortfall (e.g., Chodorow-Reich et al., 2022; Goodhart et al., 2023; Philippon, 2021; Wang and Wang, 2021).[56]

4.8 Conclusion

While the Baumol-Tobin model posits that opportunity cost proxy (the nominal interest rate) should negatively affect corporate cash holdings, recent studies provide inconsistent

[56] One may argue that cost of carry is not the common proxy in assessing the monetary policy effects. In a non-reported analysis, we replace cost of carry with the nominal 3-month T-bill rate, as the primary measure for interest rate in money demand literature. Then, we estimate the heterogenous effect of interest rate on corporate cash holdings. We find that the distributional impact of 3-month T-bill rate on cash holdings is very similar to that of cost of carry.

evidence in this regard. These studies are implicitly based on the unrealistic assumption that the effect is homogeneous across individual firms. Since firms differ in the composition of their liquid-assets portfolio and their characteristics, it is thus sensible that we assume firms manage their liquidity heterogeneously in response to opportunity cost changes. In this chapter, we study the heterogeneity in the cost of carry effect on cash holdings utilizing new advancements in machine learning methods, i.e., the causal forest. Unlike traditional parametric methods, the causal forest algorithm can detect heterogeneity without explicit assumptions on the functional form of the heterogeneity and identify non-prespecified subgroups of individuals directly affected by the treatment in a dataset.

We provide evidence that there exists substantial heterogeneity in the cost of carry effect on corporate cash holdings. That is, while most firms are negatively affected by opportunity cost measure, in line with theoretical predictions, some firms are neutral, and some experience a positive effect. Our results can explain the contradictory results on the empirical relationship between money demand and opportunity cost in prior literature. Our findings have important policy implications as well. Our cross-sectional analysis reveals that lifting Regulation Q in the early 1980s had a prolonged effect on the equilibrium relation between cash holdings and cost of carry, so that the heterogeneity in the cost of carry effects has become more pronounced over decades. This could be a sign of instability in the money demand function. Heterogeneous effects of cost of carry thus have important implications for academic research and policymaking.

Appendices

Appendix 2.1: The role of the cofounders

In this Appendix, we present the relationship of cash holdings, the nine drivers and our twenty-five controls or cofounders in the context of our method.

R&D spending: Equity issuance volatility and cash flow may affect cash and R&D spending at the same time. On the one hand, the empirical findings of Mclean (2011) show that equity issuance proceeds increase cash saving, and they are volatile sources of finance. Brown and Petersen (2011) provide evidence that in times of high volatility in equity issuance (i.e., 1998-2000 and 2000-2002) firms' R&D spending dramatically changes. Additionally, Brown et al. (2012), argue that firms follow a hierarchy to finance R&D investments. They start with internal cash flow funds, and after exhausting the internal finance they switch to expensive external finance. Owing to information asymmetry and substantial flotation costs, Brown et al. (2012) argue that external finance is not a perfect substitute for internal finance. Thus, firms often rely on internal cash flow to raise the required funds for their R&D investments. On the other hand, according to main theories of cash holdings (e.g., free cash flow, trade-off theory and pecking-order theory), firms adjust their level of cash in response to cash flow (Bates et al., 2009; Ferreira and Vilela, 2004; Opler et al., 1999).

Tangible assets: Firm size and sale of PPE affect cash holdings and tangibles at the same time. There are economies of scale in cash management (e.g., Bates et al., 2009). So, according to the trade-off model, firm size negatively affects corporate cash reserves (Bigelli and Sánchez-Vidal, 2012). Garmaise's (2008) findings show that firm size has a statistically significant effect on the capital-to-labor ratio. By stating that tangible assets of a form are correlated with the use of machinery and equipment and labor configuration, Lei et al. (2018) utilize the capital-to-labor ratio as an instrumental variable for tangible assets.

To investigate the impact of asset redeployability, which is related to alternative uses of assets outside the firm, on the choice between bank debt and public debt, Chen et al. (2020) apply the value of sale of PPE as an instrument for the asset redeployability measure. This analysis implies the association between sale of PPE and asset redeployability, which itself is closely related to tangible assets. Also, the asset sales hypothesis posits that money generated from asset sales can be considered as a substitute for external financing; as a result, selling assets in the short term can lead to an increase in firms' cash reserves (Subramaniam et al., 2011).

Cost of carry: Cash flow affects cash holdings and cost of carry at the same time. According to the trade-off (pecking-order) theory, we expect a negative (positive) relation between cash flow and cash holdings (Ferreira and Vilela, 2004). On another note, firms with higher cash flows are less likely to be financially constrained; this could lead to a positive association between cash flow and the short-term investment-to-total cash ratio (i.e., $(CHE - CH)/CHE = 1 - CH/CHE$), as a measure for cash composition (Cardella et al., 2021). From this, cash flow directly affects cost of carry. Just recall that cost of carry, as a measure for opportunity costs, is determined by cash composition (i.e., $T - bill\,rate \times CH/CHE$) (Azar et al., 2016).

Diversification: Firm size and capital expenditure simultaneously affect cash and diversification. Larger firms hold less cash (Bigelli and Sánchez-Vidal, 2012). It is also generally accepted that larger firms try to be diversified firms and expand their operations (Bakke and Gu, 2017). Campa and Kedia (2002) model the firm's decision to diversify as a function of firm characteristics, including capital expenditure. They argue that firms with a high level of investment in current operations are less likely to diversify.

If capital expenditures create assets that can be used as collateral, it can reduce the need for saving cash, because the firm can use the assets created to finance the investment projects (Bates et al., 2009). Moreover, if we consider capital expenditures as an indicator of financial crisis, they would be positively related to cash.

Tax costs of repatriating earnings: Foreign income affects cash and tax costs of repatriating earnings at the same time. Firms with more foreign income may hold more cash. First, because of the time interval between making money and consuming it, there exists a mechanical positive relation between cash holdings and income. Second, firms with more international involvement may hold more precautionary savings if investment opportunities in other countries are greater or more volatile than domestic opportunities (Foley et al., 2007). Foreign income is also an ingredient in computing our proxy for tax costs of repatriating earnings. So, the effect of foreign income ratio on tax costs is expected (Foley et al., 2007).

Debt maturity: Cash holdings and debt maturity are affected by market-to-book ratio and net debt issuance at the same time. Precautionary motive firms with high market-to-book ratios, as a measure of growth opportunities, hold more cash (Opler et al., 1999). Similarly, firms with high investment opportunities will issue more short-term debt to reduce the underinvestment problems associated with long-term debt, an argument consistent with the contracting cost-based theories of debt maturity (Byun et al., 2021).

According to Harford et al. (2014), issuing debt typically lengthens the maturity of a firm's debt. Empirical evidence of He and Wintoki (2016) and Harford et al. (2014) indicate that net debt issuance positively affects corporate cash holdings.

Intangibles: Acquisition activity and financial leverage may affect cash and intangibles at the same time. Marwick et al. (2020) introduce acquisition as a firm-specific characteristic that may confound the relation between cash holdings and organizational capital (as a component of intangible capital in our study). Acquisition activity is always considered as a fundamental determinant of corporate cash holdings (e.g., Bates et al., 2009; Opler et al., 1999). A strong relationship between cash holdings and making acquisitions is also documented by Harford (1999). He empirically shows that firms with larger cash holdings engage in more value-destroying acquisition activities.

Geng et al. (2020) investigate the effect of reporting credibility on intangible investment. In their analysis, they utilize leverage to capture the effects of firms' capital structure on intangible capital investment. Their empirical evidence shows that leverage has a statistically significant effect on intangible investment. According to the substitutability theory of Acharya et al. (2007), a positive relation between cash holdings and leverage is expected. Furthermore, financial distress associated with leverage suggests a negative link between cash holdings and leverage, as firms use their cash reserves to reduce the level of debt (Bates et al., 2009).

Relationship with customers: Acquisition activity simultaneously affects cash and relationship with customers. By utilizing data from private loan contracts between firms and their banks, Campello and Gao (2017) investigate the impact of customer concentration on several features of bank loans, including interest rate spreads, maturity and the number of restrictive covenants. In their analysis, they use mergers and acquisitions activity in customers' industries as an instrument for customer concentration (one of the main proxies for relationship with customers is based on the Herfindahl-Hirschman index of sales to major customers, which measures customer concentration, e.g., Nguyen et al., 2021; Dhaliwal et al., 2016). Campello and Gao's (2017) findings show that following high levels of M&A activity in downstream industries, firms observe higher levels of customer concentration. Similarly, acquisition activity has an important role in corporate cash management. It is considered one of the fundamental control variables in all cash studies (e.g., Bates et al., 2009; Opler et al., 1999).

Multinationality: Profitability and leverage affect cash and multinationality at the same time. Aabo et al. (2015) utilize firm-specific variables including profitability, measured by income before extraordinary items divided by total assets, to estimate the probability that a firm is involved in international operations and is going to diversify its business geographically. They provide evidence that low profitability makes firms multinational. Similarly, Elyasiani and Zhang (2015) show that profitability has a statistically significant positive effect on US firms' cash ratio.

Aabo et al. (2015) indicate that financial leverage reduces the likelihood of firms' cross-border activities. Acharya et al. (2007) and Bates et al. (2009) argue that there is both a positive and a negative effect of leverage on cash holdings. Furthermore, Fernandes and Gonenc (2016) employ leverage in panel autoregressive GMM estimation as a variable that may confound the interrelation between cash holdings and multinationality.

Appendix 2.2: Gradient Boosting

Gradient boosting is a sequential tree-based algorithm to find the best fitter based on a loss function, such as squared errors, absolute deviation, etc. (Hastie et al., 2009). The following algorithm is based on James et al. (2013). Suppose *B*, *d*, and *s* represent the number of trees to be grown, interaction depth between covariates, and shrinkage parameter, respectively. Assume we want to fit nuisance function *m* using a sample from (X_i, D_i) where D_i is one of the under-investigated drivers and X_i contains confounders in sample *i*th.[57]

1) Set $\widehat{m}(X) = 0$ and $r_i = D_i$ for all *i* in training set.

2) For *b*=1, …, *B*, repeat:

    a) Fit a regression tree $\widehat{m_b}$ with depth *d* to the training data (*X*, *r*).

    b) Update $\widehat{m}$ by adding a shrunken version of the new tree ($\widehat{m}(X) + s.\widehat{m_b}(X)$))

    c) Update the residuals ($r_i - s.\widehat{m_b}(X_i)$)

2) Output the boosted model ($\widehat{m}(X) = \sum_{b=1}^{B} s.\widehat{m_b}(X)$)

For more details on gradient boosting, see Hastie et al. (2009) and James et al. (2013).

[57] Recall that in DML, we have two nuisance functions (i.e., *m* and *g*). The estimation of these two functions is based on a sample from (*X*, *D*) and (*X*, *Y*), respectively. We apply the gradient boosting on both samples independently.

Appendix 2.3: Variable definition

Data item names in corresponding databases are in parentheses.

Cash proxies: Following Itzkowitz (2013), Bates et al. (2009) and Foley et al. (2007), our primary cash measure is logarithm of the ratio of cash and short-term investment (item che) to net assets (i.e., book value of assets (item at) minus cash and short-term investment). As an alternative proxy, following Bates et al. (2009) and Azar et al. (2016), we also consider the ratio of cash to assets in sensitivity analysis.

R&D spending: Following He and Wintoki (2016), we use the ratio of R&D spending (item xrd) to total assets (item at) as the proxy for research and development expenditures.

Intangible capital: Following Gu (2017), intangible capital is equal to the sum of intangible assets (item intang / item at) and accumulated sum of R&D spending (item xrd / item at), as a measure of knowledge capital, plus 30% SG&A spending (item xsga / item at), as a measure of organizational capital, using the perpetual inventory method (PIM) of Peters and Taylor (2017). The PIM to estimate the accumulated sum of R&D spending for firm *i* at time *t* would be:

$$G_{it}=(1-d_{RD}) * G_{i,t-1} +RD_{it}$$

Where G_{it} is the knowledge capital and d_{RD} is the depreciation rate, which, following Gu (2017), we set to 15%. The initial value ($KC_{i,0}$) in the equation above is zero. Organizational capital is estimated using the equation above in an analogous manner, by substituting RD with SG&A expenditure.[58]

Tangible assets: Following Lei et al. (2018), tangible assets is equal to the sum of (0.715× receivables (item rect)), (0.547×inventory (item invt)) + (0.535×property, plant, and equipment (item ppent)), deflated by total assets (item at).

Tax costs of repatriating earnings: A main proxy for the tax burden associated with repatriations is computed by first subtracting foreign taxes paid (item txfo) from the product of a firm's foreign pre-tax income (item pifo) and its marginal effective tax rate. Then the maximum of this difference or zero is scaled by total assets (item at) (Foley et al., 2007). But according to Graham (1996), estimates of marginal effective tax rates require making several assumptions. Thus, following Foley et al. (2007), we utilize the US statutory rates in the main proxy in place of marginal tax rates. Statutory tax rate is retrieved from the OECD

[58] This is consistent with the new approach adopted by the Bureau of Economic Analysis (BEA) in 2013 for the National Income and Product Accounts (NIPA) (Falato et al., 2020).

Tax Database.[59] It must be noted that *Pretax Income—Foreign* (pifo item in Compustat) and *Income Taxes—Foreign* (txfo item in Compustat) are only reported by some firms. Thus, according to Foley et al. (2007), we set their missing values to zero.

Cost of carry: Cost of carry is calculated as a lagged 10-year average of non-interest-bearing assets (item ch) as a share of total liquid assets (item che) multiplied by the 3-month T-bill rate (Azar et al., 2016).[60]

Debt maturity: Following Custódio et al. (2013), debt maturity is calculated by long-term debt (item dltt) minus debt maturing in 2 and 3 years (item dd2 + item dd3) to total debt (item dltt + item dlc). We drop firm-year observations with maturity debt less than 0 or greater than 1, in line with Custódio et al. (2013).

Diversification: Following Duchin (2010) and Bakke and Gu (2017), we measure the level of industrial diversification of a firm using the number of business segments (stype = 'BUSSEG') reported by the firm. The data for this variable come from Compustat's Historical Segments dataset.

Relationship with customers: Following Itzkowitz (2013), relationship with customers is defined by the sum of a firm's sales to its major customers (item salecs) (a customer with generated revenue greater than 10% of revenue of the firm) divided by total sales (item sale). The required data for a firm's sales to its customers are from Compustat's Customer Segments. Since 1976, the Statement of Financial Accounting Standards No. 14 (SFAS 14) of the Financial Accounting Standard Board (FASB) has required a supplier to disclose external customers that individually account for 10% or more of its revenues. However, suppliers often voluntarily report customers that account for less than 10% of sales. Because these disclosures are voluntary, following Itzkowitz (2013) and Dhaliwal et al. (2016), we do not include these customers in our calculations to reduce concerns of a potential 'selection bias'.

Multinationality: To measure international involvement (multinationality) of a firm, following Fernandes and Gonenc (2016), we utilize the fraction of foreign sales (sales for GEOTP = 3) to total sales (item sale). The data for foreign sales are retrieved from Compustat's Historical Segments.

Firm size: Following Bates et al. (2009) and Opler et al. (1999), we use the natural logarithm of book value of assets (item at) as a measure for firm size.

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[59] https://stats.oecd.org/
[60] https://fred.stlouisfed.org/

Growth opportunities: As a proxy for investment opportunities, we apply market to book ratio, defined as market value of equity plus book value of assets (item at) minus book value of equity (item ceq) divided by book value of assets (item at), where market value of equity is equal to multiplication of fiscal share price (item prcc_f) and number of shares outstanding (item csho) (Bates et al., 2009).

Financial leverage: We measure leverage as total long-term debt (item dltt) plus total debt in current liabilities (item dlc) divided by book value of assets (item at) (Bates et al., 2009).
Dividends: This is a dummy variable which is equal to 1 if in a year the firm pays a common dividend (item dvc), and zero otherwise (Bates et al., 2009, Opler et al., 1999).

Cash flow: We measure cash flow, following Bates et al. (2009), as operating income before depreciation (item oibdp), less interest expense (item xint), income taxes (item txt) and dividends (item dvc), divided by book value of total assets (item at).

Cash flow volatility: Cash flow volatility is the average of the standard deviation of the cash flow ratio (introduced above) using a 10-year rolling window if there are at least 3 observations for the firm by two-digit SIC code (Bates et al., 2009).
Net working capital: As a substitute for cash, net working capital is calculated by the ratio of working capital (current assets (item act) minus current liabilities (item lct)) less cash and cash equivalents (item che) to book value of assets (item at) (Bates et al., 2009).

Acquisitions: This variable is calculated by the ratio of acquisitions (item aqc) to book value of assets (item at) (Bates et al., 2009).

Capital expenditure: To measure this variable, we utilize the ratio of capital expenditures (item capx) to total assets (item at), in line with Bates et al. (2009).

Appendix 2.4: Simultaneous causal effects of drivers: Alternative learners

	Effect (1)	Romano-Wolf (2)	Benjamini-Yekutieli (3)	Bonferroni (4)
Panel A: Regression trees				
R&D spending	0.247 (42.039***)	0.000	0.000	0.000
Intangible assets	-0.130 (19.618***)	0.000	0.000	0.000
Tangible assets	-0.422 (61.677***)	0.000	0.000	0.000
Tax costs of repatriating earnings	0.021 (3.633***)	0.001	0.001	0.003
Cost of carry	-0.071 (13.513***)	0.000	0.000	0.000
Debt maturity	0.053 (9.945***)	0.000	0.000	0.000
Diversification	-0.023 (4.969***)	0.000	0.000	0.000
Relationship with customers	0.009 (1.984**)	0.046	0.134	0.425
Multinationality	0.054 (11.513***)	0.000	0.000	0.000
Controls			Yes	
N. observations			35,294	
Panel B: LASSO				
R&D spending	0.255 (42.371***)	0.000	0.000	0.000
Intangible assets	-0.209 (29.995***)	0.000	0.000	0.000
Tangible assets	-0.437 (66.629***)	0.000	0.000	0.000
Tax costs of repatriating earnings	0.023 (4.766***)	0.000	0.000	0.000
Cost of carry	-0.110 (21.962***)	0.000	0.000	0.000
Debt maturity	0.081 (16.609***)	0.000	0.000	0.000
Diversification	0.003 (0.795)	0.428	1.000	1.000
Relationship with customers	0.016 (3.762***)	0.000	0.001	0.002
Multinationality	0.110 (24.245***)	0.000	0.000	0.000
Controls			Yes	
N. observations			35,294	

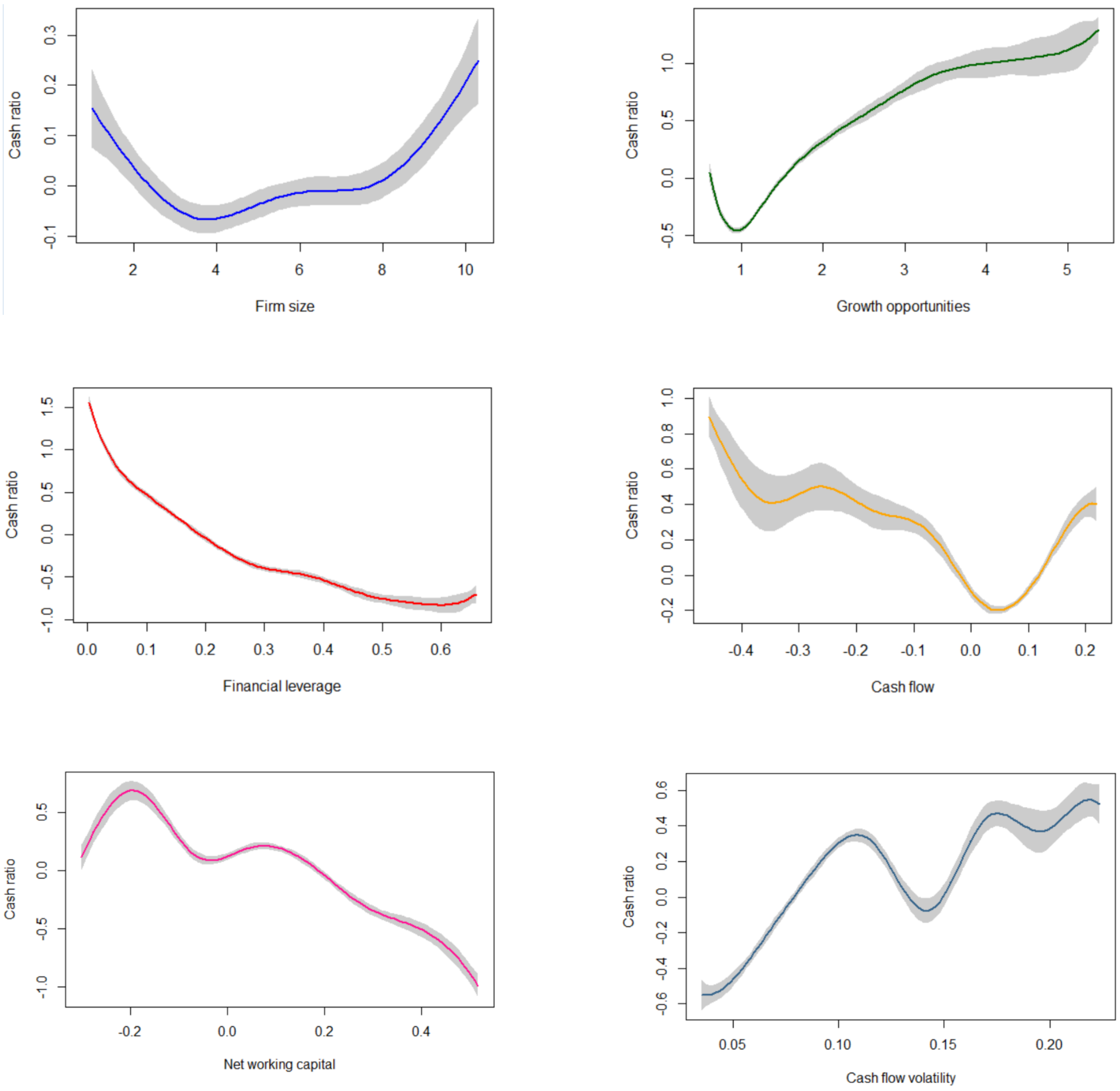
Note: The table reports the simultaneous causal effect of the drivers obtained from the double machine learning (DML) utilizing four-fold crossfitting. The nuisance functions (*g* and *m* in Equations (2.1) and (2.2)) are learned with the regression trees (Panel A) and LASSO (Panel B). Hyperparameters in both cases (shrinkage and complexity parameter) are selected by 10-fold cross-validation (CV). Estimated effects are based on the 100 splits. The dependent variable is the natural logarithm of cash-to-net assets. The initial sample is from Compustat covering 1980-2019. Financial (SIC code 6000-6999) and utility firms (SIC codes 4900-4999) are excluded from the sample. We then supplement it with two other datasets including Historical Segments and Customer Segments. The final sample consists of 35,294 firm-year observations from 6,737 unique firms. To mitigate the influence of outliers, all variables are winsorized at the 2nd and 98th percentiles. Variable definitions are provided in Appendix 2.3. *, ** and *** denote significance at the 10%, 5% and 1% respectively.

Appendix 2.5: Simultaneous causal effects of drivers: Alternative cash proxy

	Effect (1)	Romano-Wolf (2)	Benjamini-Yekutieli (3)	Bonferroni (4)
Panel A: *d=1 & s=0.1*				
R&D spending	0.295 (44.160***)	0.000	0.000	0.000
Intangible assets	-0.261 (-35.684***)	0.000	0.000	0.000
Tangible assets	-0.561 (-76.911***)	0.000	0.000	0.000
Tax costs of repatriating earnings	0.043 (6.895***)	0.000	0.000	0.000
Cost of carry	-0.054 (-12.972***)	0.000	0.000	0.000
Debt maturity	0.055 (11.125***)	0.000	0.000	0.000
Diversification	-0.051 (-12.285***)	0.000	0.000	0.000
Relationship with customers	0.013 (2.891***)	0.004	0.011	0.035
Multinationality	0.063 (11.421***)	0.000	0.000	0.000
Controls			Yes	
N. observations			35,294	
Panel B: d=2 & s=0.05				
R&D spending	0.300 (45.397***)	0.000	0.000	0.000
Intangible assets	-0.226 (-32.052***)	0.000	0.000	0.000
Tangible assets	-0.585 (-78.081***)	0.000	0.000	0.000
Tax costs of repatriating earnings	0.041 (6.359***)	0.000	0.000	0.000
Cost of carry	-0.061 (-14.774***)	0.000	0.000	0.000
Debt maturity	0.059 (12.430***)	0.000	0.000	0.000
Diversification	-0.047 (-11.747***)	0.000	0.000	0.000
Relationship with customers	0.015 (3.599***)	0.000	0.001	0.003
Multinationality	0.049 (9.304***)	0.000	0.000	0.000
Controls			Yes	
N. observations			35,294	

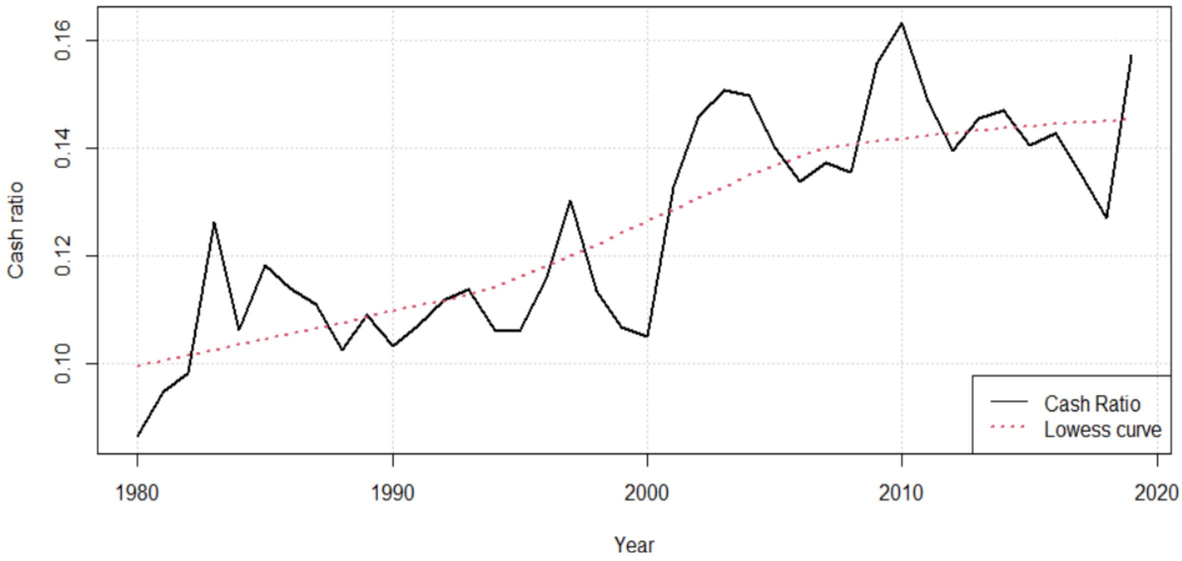
Note: The table reports the causal effects of the drivers simultaneously, obtained from double machine learning (DML) utilizing four-fold crossfitting. The nuisance functions (*g* and *m* in Equations (2.1) and (2.2)) are learned with the gradient boosting method under different values of interaction depth (*d*) and shrinkage (*s*): (*d*=1, *s*=0.1) and (2, 0.05). The optimal number of trees is selected by 10-fold cross-validation (CV). Estimated effects are based on the 100 splits. Adjusted *p*-values in columns (2)-(4) for joint significance testing are based on the multiplier bootstrap procedure (Chernozhukov et al., 2013) in combination with the step-down method of Romano and Wolf (2005), and Benjamini and Yekutieli (2001) and Bonferroni correction over 1,000 repetitions. The dependent variable is the ratio of cash and short-term investment to assets. Variable definitions are provided in Appendix 2.3. *, ** and *** denote significance at the 10%, 5% and 1% respectively.

Appendix 2.6: Cash holdings and firm characteristics



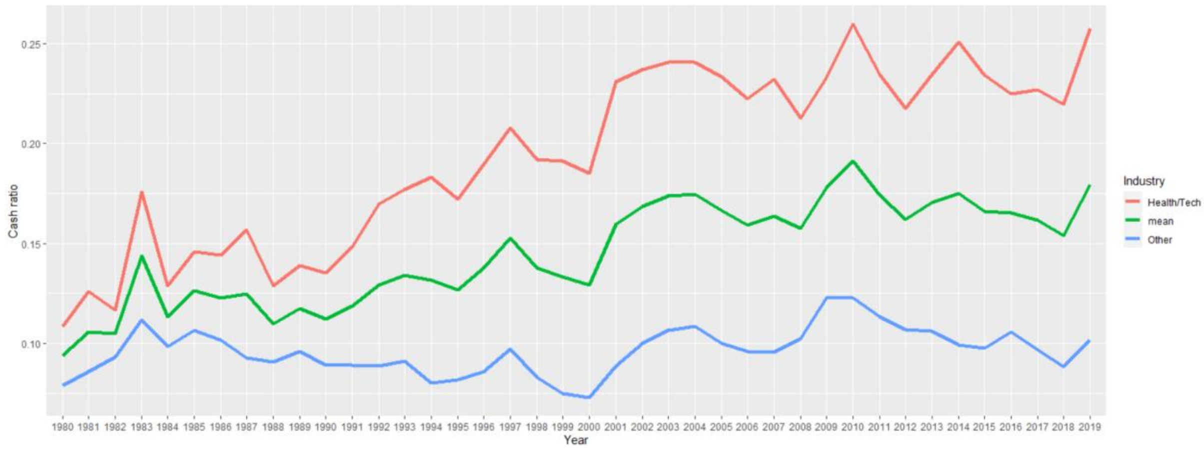
Note: The figure shows marginal relations between cash holdings and selected firm characteristics (firm size, growth opportunities, financial leverage, cash flow, net working capital, cash flow volatility). The dependent variable is the logarithm of cash-to-net assets ratio. The sample is from Compustat over the period. We exclude financial (SIC code 6000-6999) and utility firms (SIC codes 4900-4999). The curves are fitted by generalized additive model using the P-spline smoothing technique. We use the generalized cross-validation (GCV) to estimate the smoothing parameter. The grey region shows 95% Bayesian confidence intervals. We provide variable definitions in Appendix 2.3.

Appendix 2.7: Cash-to-asset ratio time series



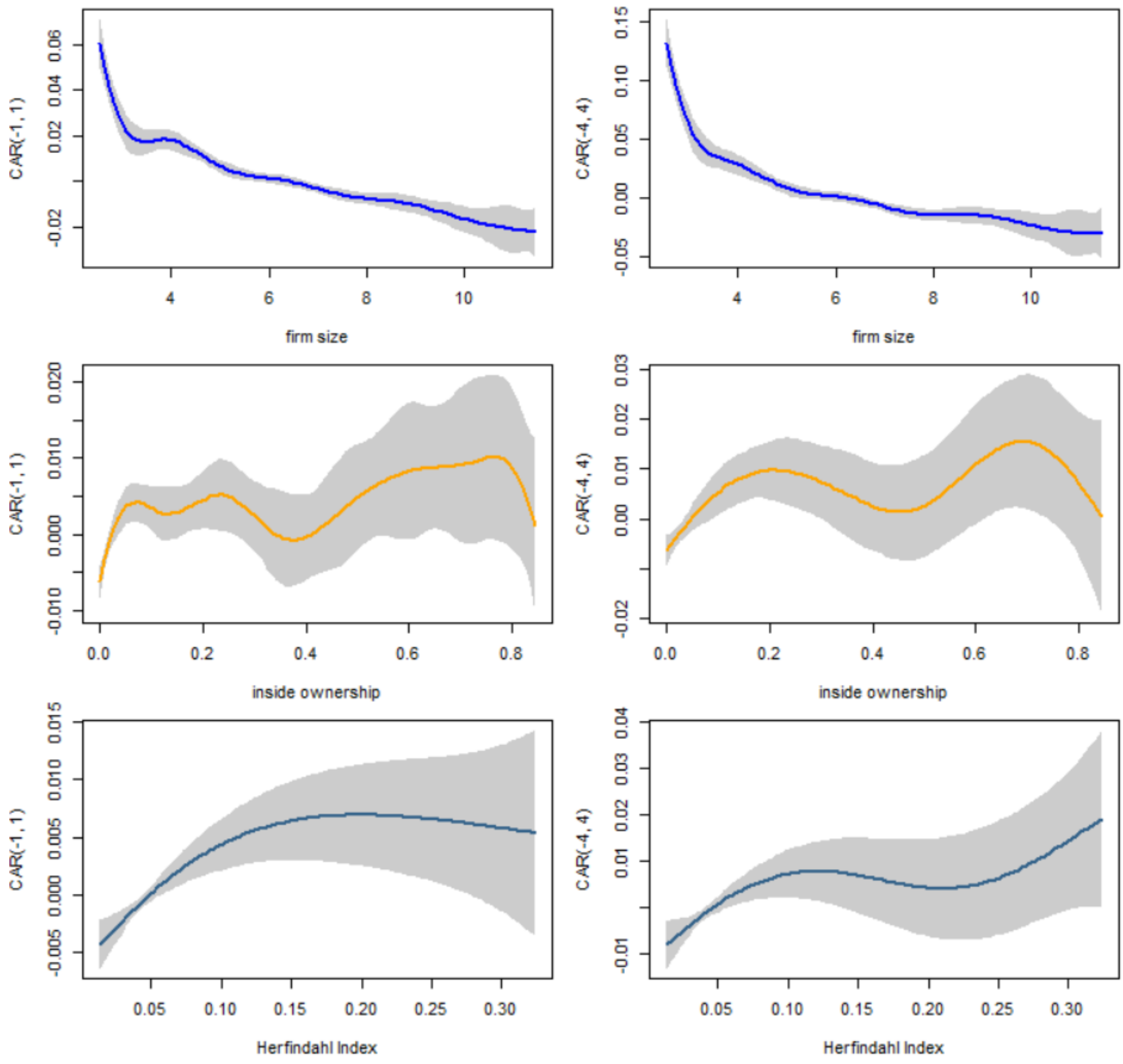
Note: The figure shows the time series of US firms' cash-to-assets ratio (solid line) and the lowess (LOcally WEighted Scatter-plot Smoother) curve (dashed line) to highlight the trend of the time series. The initial sample is from Compustat, covering 1980-2019. Financial (SIC code 6000-6999) and utility firms (SIC codes 4900-4999) are excluded from the sample. We then supplement it with two other datasets including Historical Segments and Customer Segments

Appendix 2.8: Cash-to-asset ratio time series by industry



Note: The figure shows the time series of US firms' cash-to-assets ratio between 1980-2019 by two sectors: healthcare and technology industries (red line), and other industries (blue line). Industry classification is based on the Fama-French 12-industries. The green line is for the mean cash-to-assets ratio over all industries. The initial sample is from Compustat. Financial (SIC code 6000-6999) and utility firms (SIC codes 4900-4999) are excluded from the sample. We then supplement them with two other datasets including Historical Segments and Customer Segments**.**

Appendix 3.1: Cumulative abnormal return and selected characteristics



Note: The figure shows marginal relations between $CAR(-1,1)$, $CAR(-4,4)$, and selected firm characteristics (firm size, inside ownership, Herfindahl index). The curves are fitted by P-spline smoothing technique. We use the generalized cross-validation (GCV) to estimate the smoothing parameter. The grey region shows 95% Bayesian confidence intervals.

Appendix 3.2: M&A return determinants

Variable	Description & Source
Target status	Dummy variable (1 if the target firm is a public firm, 0 otherwise) (Source: SDC)
Method of payment	Dummy variable (1 if method of payment was 100% cash, 0 otherwise) (Source: SDC)
Mixed offer	Dummy variable (1 if the deal was financed both with cash and stocks, 0 otherwise) (Source: SDC)
Bidder size	Natural logarithm of acquirer’s market value, CPI adjusted, 4 weeks prior to announcement (Source: SDC)
Bidder's Q	Market value of assets (total debt plus market value of equity) to the book value of assets (Source: Compustat)
Bidder market-to-book value	Market value of equity to book value of equity (Source: Compustat)
Relative size	Relative transaction value over acquirer’s market value (Source: SDC)
Bidder PE ratio	Closing share price to earnings per share excluding extraordinary items (Source: Compustat)
Serial acquirers	Dummy variable (1 if 5 or more deals within 3 years; 0 otherwise). (Source: SDC)
Diversifying	Dummy variable (1 if the acquiring and target firm belong to the same 2-digit SIC code, 0 otherwise) (Source: SDC)
Tender-offer	Dummy variable (1 if tender offer, 0 otherwise) (Source: SDC)
Leverage	Long-term debt plus debt in current liabilities deflated by common equity (Source: Compustat)
Free cash flow	Operating income before depreciation minus interest expense minus income taxes plus change in deferred taxes minus preferred dividends minus common dividends divided by long-term debt plus debt in current liabilities plus preferred stock plus common equity (Source: Compustat)
Cash	Cash and short-term investments divided by total assets
Competing	Dummy variable (1 if the offer is made in a multiple-bidder contest, 0 otherwise) (Source: SDC)
Deal Attitude:	Dummy variable (1 if hostile, 0 otherwise) (Source: SDC)
Target Advisors	Dummy variable (1 if the target firm used investment bank advisor; 0 otherwise) (Source: SDC)
Bidder Advisors	Dummy variable (1 if the bidder firm used investment bank advisor; 0 otherwise) (Source: SDC)
Sigma	Standard deviation of the bidding firm’s market-adjusted daily returns over the period beginning 205 and ending 6 days before deal announcement (Source: CRSP)
Bidder Run-up	Market-adjusted buy-and-hold return of the bidding firm's stock over the period beginning 205 days and ending 6 days prior to the announcement date (Source: CRSP)

Earnings growth forecasts	The standard deviation of the long-term earnings growth forecasts (LTG) (Source: I/B/E/S)
Bidder age	Number of years since first trading date on CRSP (Source: CRSP)
High-tech deal	Dummy variable (1 if the acquiring firm is a tech firm, 0 otherwise) (Source: SDC)
Sin industry dummy	Dummy variable (1 if the acquiring firm is not in a sin industry and the target firm is in a sin industry, 0 otherwise) (Source: CRSP)
Initial industry bidder	Dummy variable (1 if the firm is the first firm in a four-digit SIC code to make a bid after a minimum dormant period (a period without bids by other firms in the industry) of twelve months, 0 otherwise) (Source: CRSP)
Transaction value	Value of transaction (Source: SDC)
Acquirer's rating existence	Dummy variable (1 if the bidding firm has a credit rating one month prior to the acquisition announcement, 0 otherwise) (Source: Compustat)
M&A liquidity	Sum of acquisitions value for each year and 2-digit SIC classification divided by the total assets of all Compustat firms in the same industry classification and year (Source: SDC & Compustat)
Acquirer's illiquidity	Illiquidity ratio from Amihud (2002)
Bidder's number of analysts	Number of analysts following the firm for the last month of the fiscal year preceding the acquisition announcement (Source: I/B/E/S)
Target's number of analysts	Number of analysts following the firm for the last month of the fiscal year preceding the acquisition announcement (Source: I/B/E/S)
Inside ownership	Shares held by the firm's officers and directors as a percentage of the firm's total shares outstanding (Source: Thomson/Refinitiv)
Interest rate spread	Spread between the average rate on commercial and industrial loans and the Federal Funds rate (Source: FRED)
Bidder's efficiency	Measured using data envelopment analysis (DEA) based on Demerjian et al.'s (2012) methodology
Bidder's managerial ability	Measured using data envelopment analysis (DEA) based on Demerjian et al.'s (2012) methodology
Bidder's efficiency ranking	Measured using data envelopment analysis (DEA) based on Demerjian et al.'s (2012) methodology
Bidder's managerial ability ranking	Measured using data envelopment analysis (DEA) based on Demerjian et al.'s (2012) methodology
Operating cash flow	Total sales minus cost of goods sold minus selling, general and administrative expense plus depreciation plus goodwill divided by market value of equity plus debt in current liabilities plus long-term debt minus cash and short-term investments)) (source: Compustat)

Dividend	Dummy variable (1 if common dividends > 0, 0 otherwise) (Source: Compustat)
Capital expenditure	Capital expenditure divided by total assets (Source: Compustat)
Sales growth	Growth rate in total sales (Source: Compustat)
Tangible assets	Total property, plant, and equipment divided by total assets (Source: Compustat)
R&D expense	Research and development spending divided by total assets. Missing values are replaced by 0 (Source: Compustat)
Merger waves	Dummy variable (1 if merger activity (number or dollar value of mergers) in a given year is at the top quartile of merger activities over the sample period, and 0 otherwise) (Source: SDC)
Market valuations	Detrended PE ratio (Source: Bob Shiller Web site (www.irrationalexuberance.com/index.htm)
Regulation-deregulation	Dummy variable (1 if regulated industry, 0 otherwise) (Source: Ovtchinnikov (2013) and Harford (2005))
Herfindahl index	Sum of squared market shares of all Compustat firms in the industry (Source: Compustat)
Policy uncertainty	The BBD index of Baker et al. (2016) (Source http://www.policyuncertainty.com/)
Geopolitical risk	The index of Caldara and Iacoviello (2022) (Source http://www.policyuncertainty.com/)

Appendix 3.3: DML estimation results of M&A return determinants recursively by year of publication

Factor	Year	Effects	t-statistics
Free Cash Flow	1991	-0.020	-1.240
Cash	1991	-0.018	-1.129
Deal Attitude: Friendly/Hostile	1991	0.005	0.716
Inside ownership	1992	-0.011	-0.773
Operating cash flow (ROA)	1992	-0.032	-1.721
Leverage	1993	0.001	0.050
Target Advisors	1996	-0.063	-4.440***
Bidder Advisors	1996	-0.054	-3.559***
Bidder Run-up	1996	-0.040	-1.789
Merger waves	1996	0.004	0.150
Regulation-Deregulation	1996	0.006	0.400
Target status	1998	-0.128	-7.405***
dividend	1999	0.001	0.083
Sales Growth	1999	-0.039	-2.703**
Herfindahl Index	2000	0.022	1.940*
High-tech deal	2001	-0.037	-1.577
Serial Acquirers	2002	-0.001	-0.755
Bidder PE	2003	0.009	0.498
Interest Rate Spread	2005	0.039	1.021
Tangible Assets	2005	-0.010	-0.527
R&D expense	2005	-0.031	-1.504
Sigma	2007	0.012	0.256
long-term earnings growth forecasts	2007	0.035	1.483
Acquirer’s Number of Analysts	2009	-0.012	-0.570
Target’s Number of Analysts	2009	-0.103	-4.092***
Market valuations	2009	0.051	2.534**
Initial industry bidder	2011	0.005	0.251
M&A Liquidity	2011	0.010	0.437
Bidder age	2012	0.033	1.665*
Acquirer’s Illiquidity	2013	0.009	0.237
Acquirer’s Rating Existence	2014	0.014	0.548
Acquirer’s Efficiency	2017	-0.069	-2.321*
Acquirer’s Efficiency ranking	2017	-0.031	-1.285
Policy uncertainty	2017	-0.102	-1.420
capital expenditure	2018	-0.001	-0.022
Sin Industry dummy	2020	-0.018	-2.135*
Acquirer’s managerial ability	2020	0.009	0.151
Acquirer’s managerial ability ranking	2020	-0.009	-0.265
GPR (Geopolitical Risk)	2022	0.067	1.139

Note: Tis table illustrates the effects of M&A return determinants using DML recursively by year of publication. The dependent variable is CAR(-1,1). In the years with more than one factor, we adjust *p*-values using Hochberg’s (1988) correction method to avoid false discoveries. Industry and year fixed effects are included.

Appendix 3.4: Factor loadings in thematic grouping

Group name	Targets	Factor loading	*z*-statistics
Bidder characteristics	Serial acquirers	0.037	2.148**
	Bidder PE	-0.002	-0.136
	Sigma	0.984	29.201***
	Bidder number of analysts	-0.154	-8.769***
	Bidder Run-up	-0.528	-22.975***
	Bidder age	-0.357	-17.965***
Deal-specific variables	Competing	0.350	8.434***
	Deal attitude	0.210	6.856***
	Transaction value	0.501	8.920***
	Mixed offer	0.147	5.015***
Accounting variables	Bidder Tobin's Q	0.437	24.267***
	Cash	0.822	48.109***
	Free cash flow	-0.171	-9.125***
	Operating cash flow	-0.378	-20.741***
	Leverage	-0.148	-7.873***
	Capital expenditure	-0.278	-15.034***
	Tangible assets	-0.472	-26.408***
	Sales growth	0.043	2.254**
	R&D expense	0.683	39.557***
Other bidder characteristics	Inside ownership	0.070	4.113***
	Bidder illiquidity	0.076	4.474***
	Bidder efficiency	-0.928	-72.189***
	Bidder managerial ability	-0.968	-77.897***
	Bidder efficiency ranking	-0.728	-49.856***
	Bidder managerial ability ranking	-0.833	-60.663***
	Acquirer’s rating existence	-0.056	-3.292***
Industry characteristics	Herfindahl index	0.408	2.974***
	High-tech deal	-0.685	-2.989***
	Initial industry bidder	0.047	1.862*
	Sin industry dummy	0.041	1.644
Market characteristics (Related to M&As)	Merger waves	1.364	1.217
	Market valuations	0.046	1.113
	M&A liquidity	0.213	1.211
Other market characteristics (Other macros)	Policy uncertainty	0.929	21.504***
	Geopolitical risk	0.195	10.412***
	Interest rate spread	0.716	20.477***
Advisors	Target advisors	0.648	46.086***
	Bidder advisors	0.648	46.086***
Other variables	Regulation-deregulation	0.022	1.193
	Earnings growth forecasts	0.214	3.097***
	Target’s number of analysts	-0.119	-2.909***
	Dividend	-0.988	-3.187***

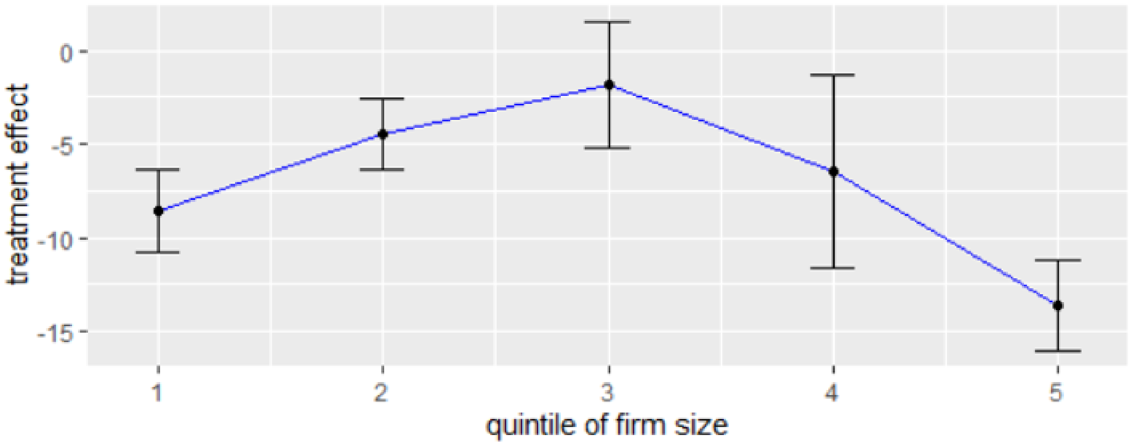
Note: This table presents the factor loadings on M&A returns determinants, thematically categorized, in a confirmatory factor analysis.

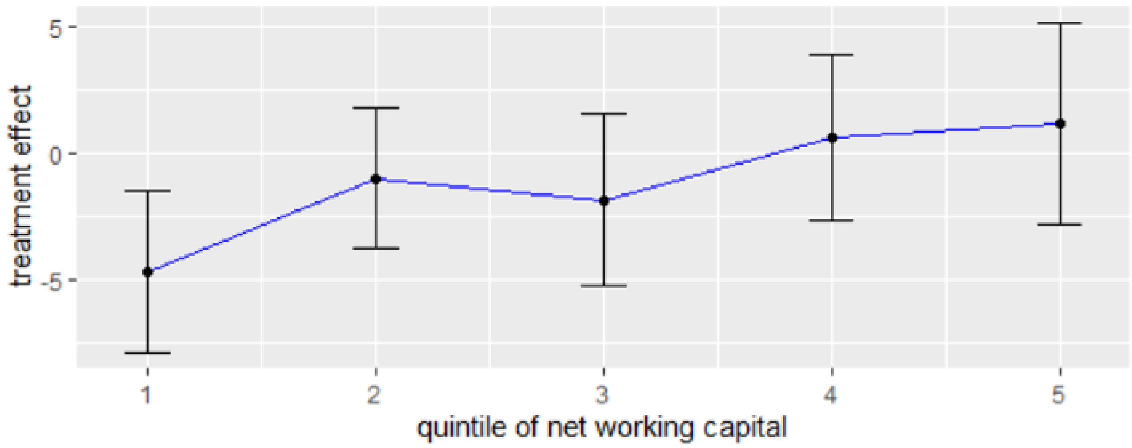
Appendix 4.1: Variables definitions

Variable	Definition
Panel A: Dependent variable	
Log Cash-to-net assets	Natural logarithm of cash and cash equivalents (che) divided by book value of net assets (at - che)
Cash-to-assets	Cash and cash equivalents (che) divided by book value of total assets (at)
Panel B: Treatment variable	
Cost of carry	$\mathrm{T} - \mathrm{Bill} \times \bar{s}$, where T-bill is the nominal 3-month T-bill rate from FRED, and $\bar{s}$ is the lagged 10-year average of non-interest-bearing assets (ch) as a share of total cash and cash equivalents (che)
Panel C: Control variable	
Firm Size	Natural logarithm of book value of total assets (at)
Market-to-book value of assets	(Book value of assets (at) - book value of equity (ceq) + market value of equity (prcc_f*csho)) divided by book value of total assets (at)
Financial leverage	(Total long-term debt (dltt) + total debt in current liabilities (dlc)) divided by book value of total assets (at)
Dividend	Dummy variable (1 if a firm pays dividends (dvc) and 0 otherwise)
Cash Flow	(Operating income before depreciation (oibdp) - interest expense (xint) - income taxes (txt) - dividends (dvc)) divided by book value of total assets (at)
Cash flow volatility	The average of the standard deviation of the cash flow-to-total assets over 10 years by two-digit SIC codes
R&D Expense	Research and development spending (xrd) divided by sales (sale). Missing values are set equal to 0.
New working capital	(Current assets (act) - current liabilities (lct) - cash and cash equivalents (che)) divided by book value of total assets (at)
Capital expenditures	Capital expenditure (capx) divided by book value of total assets (at)
Acquisitions	Acquisition expenditures (aqc) divided by book value of total assets (at)

Note: This table presents definitions of the variables. Compustat item names are provided in parentheses.

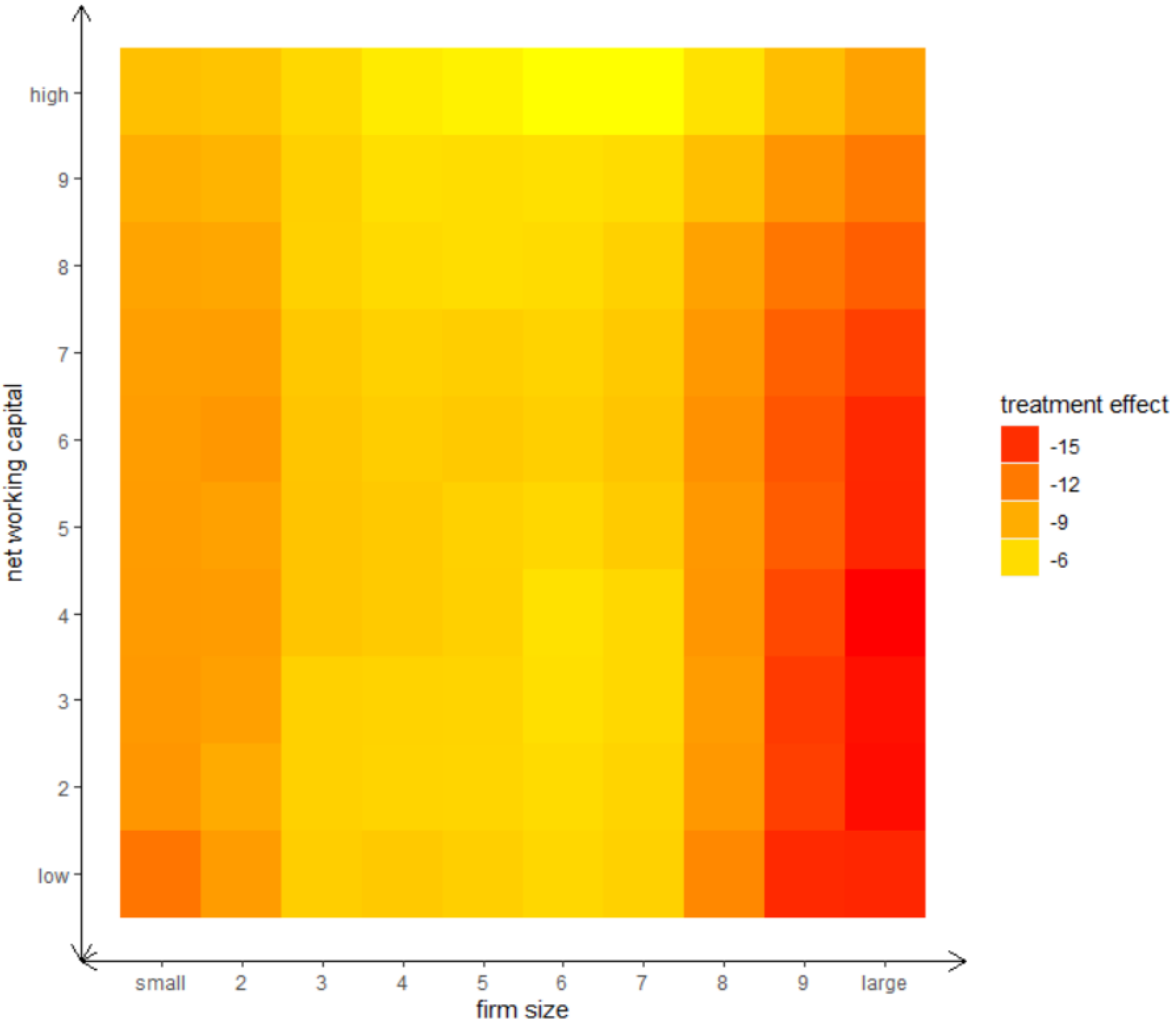
Appendix 4.2: Partial dependence plot of cost of carry effect





Note: This figure presents the partial dependence plots (PDPs), along with error bars, for firm size (upper panel) and net working capital (lower panel), as the first and second most important variables in the forest. In each plot, we vary the variable on the *x*-axis on its quintiles, while other covariates are fixed to their median values.

Appendix 4.3: Heatmap of cost of carry effect on cash holdings by firm size and net working capital



Note: This figure presents the heatmap of cost of carry effect on cash holdings by deciles of firm size (on *x*-axis) and net working capital (on *y*-axis), as the first and second most important variables in the forest. Cash balances of large firms with low net working capital are the most sensitive to cost of carry.

Appendix 4.4: Cross-sectional heterogeneity in cost of carry effect: Alternative cash measure

Panel A: *Summary statistics*

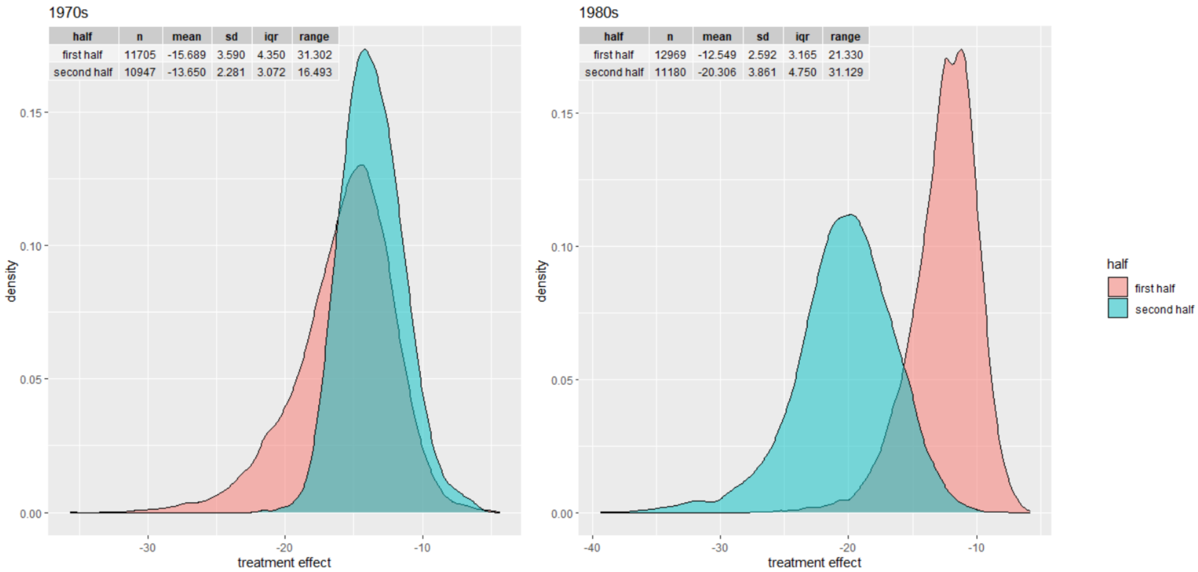
Decade	N	Mean	SD.	Min.	Max.	Range	Test of heterogeneity	
							β^C	β^D
1970s	22,652	-0.947	0.352	-2.894	-0.270	2.624	1.015 (21.308***)	1.268 (6.522***)
1980s	24,149	-2.006	1.905	-20.758	-0.227	20.531	0.995 (10.646***)	1.114 (4.699***)
1990s	39,586	-3.087	2.815	-30.700	9.894	40.594	1.019 (8.301***)	0.610 (2.452***)
2000s	39,510	-4.000	4.305	-39.398	16.588	55.985	0.943 (5.379***)	0.492 (1.583*)
2010s	32,532	-10.071	15.252	-108.586	98.958	207.544	1.041 (4.623***)	0.933 (3.265***)

Panel B: *Kolmogorov-Smirnov test*

	1970s	1980s	1990s	2000s
1980s	0.388***			
1990s	0.644***	0.261***		
2000s	0.656***	0.318***	0.113***	
2010s	0.675***	0.427***	0.300***	0.224***

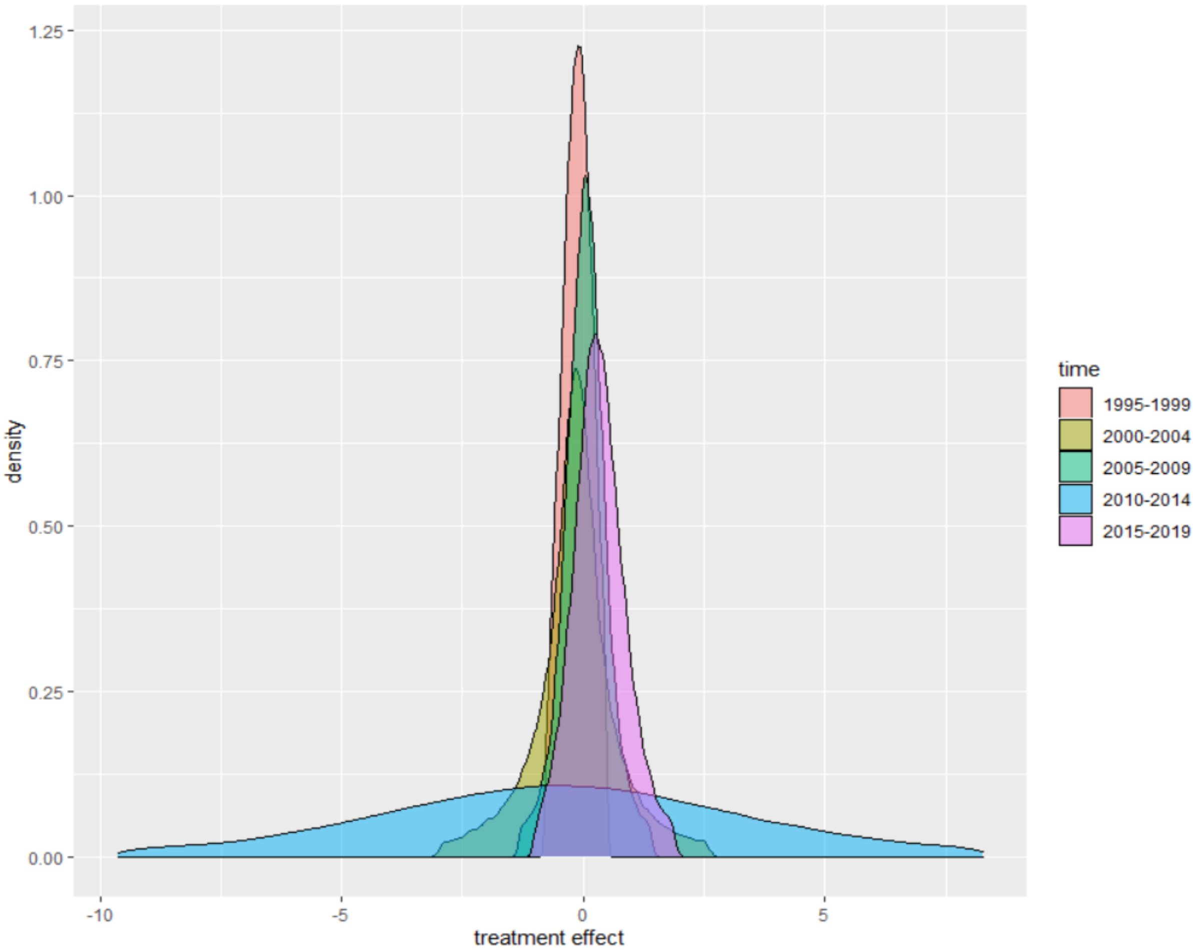
Note: This table reports the summary statistics of the firm-level effect of cost of carry on cash holdings using cluster-robust (by firms) causal forest for five decades (1970s, 1980, 1990s, 2000s, and 2010s) in Panel A. The results of the heterogeneity test based on the best linear predictor (BLP) are presented in the last two columns. Two-sample Kolmogorov-Smirnov (KS) test results are reported in Panel B. The dependent variable is cash-to-assets ratio. The confounders set consists of ten covariates (firm size, market-to-book ratio, financial leverage, dividend, cash flow, cash flow volatility, R&D, new working capital, capital expenditures, and acquisitions). The sample consists of 158,429 firm-year observations from 17,062 unique firms retrieved from Compustat over 1971-2019. Financial (SIC code 6000-6999) and utility firms (SIC codes 4900-4999) are excluded from the sample. To mitigate the influence of outliers, all variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix 4.1. *, **, and *** denote significance at 10%, 5%, and 1% respectively.

Appendix 4.5: Heterogeneous effect of cost of carry in the first and second half of the 1970s and 1980s



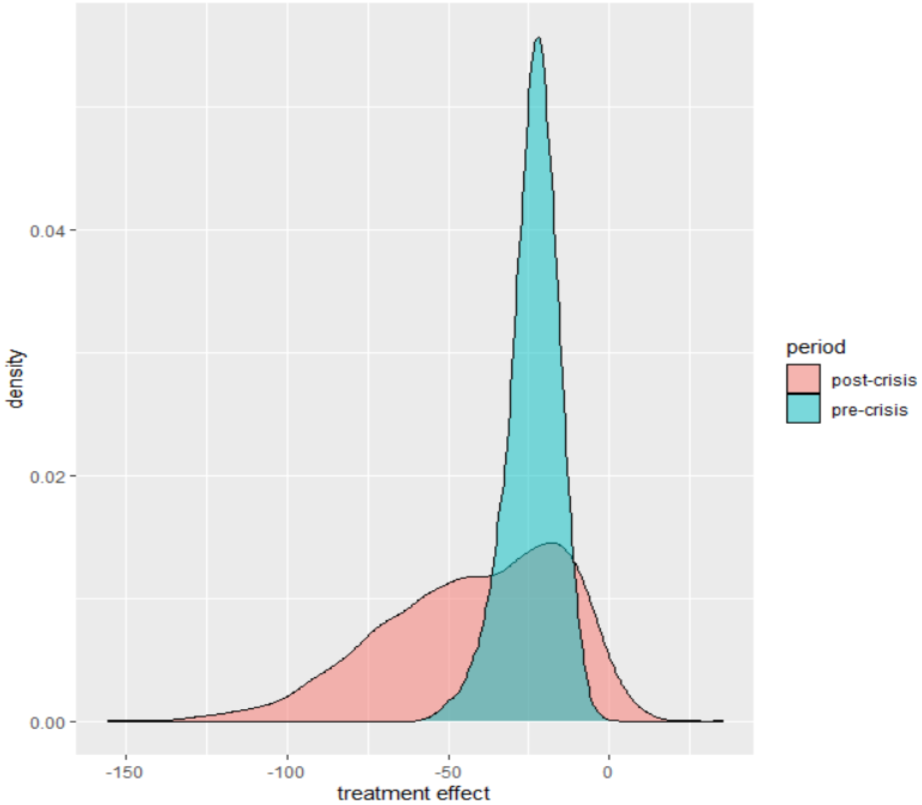
Note: This figure compares the distribution of firm-level cost of carry effect on log of cash-to-net assets ratio, estimated by the causal forest method, between the first and second half of the 1970s and 1980s. Summary statistics (number of observations, mean, standard deviation, interquartile range, and range index) of the estimated effects are reported on top of the figures.

Appendix 4.6: Heterogeneous effect of raw interest rate on cash holdings



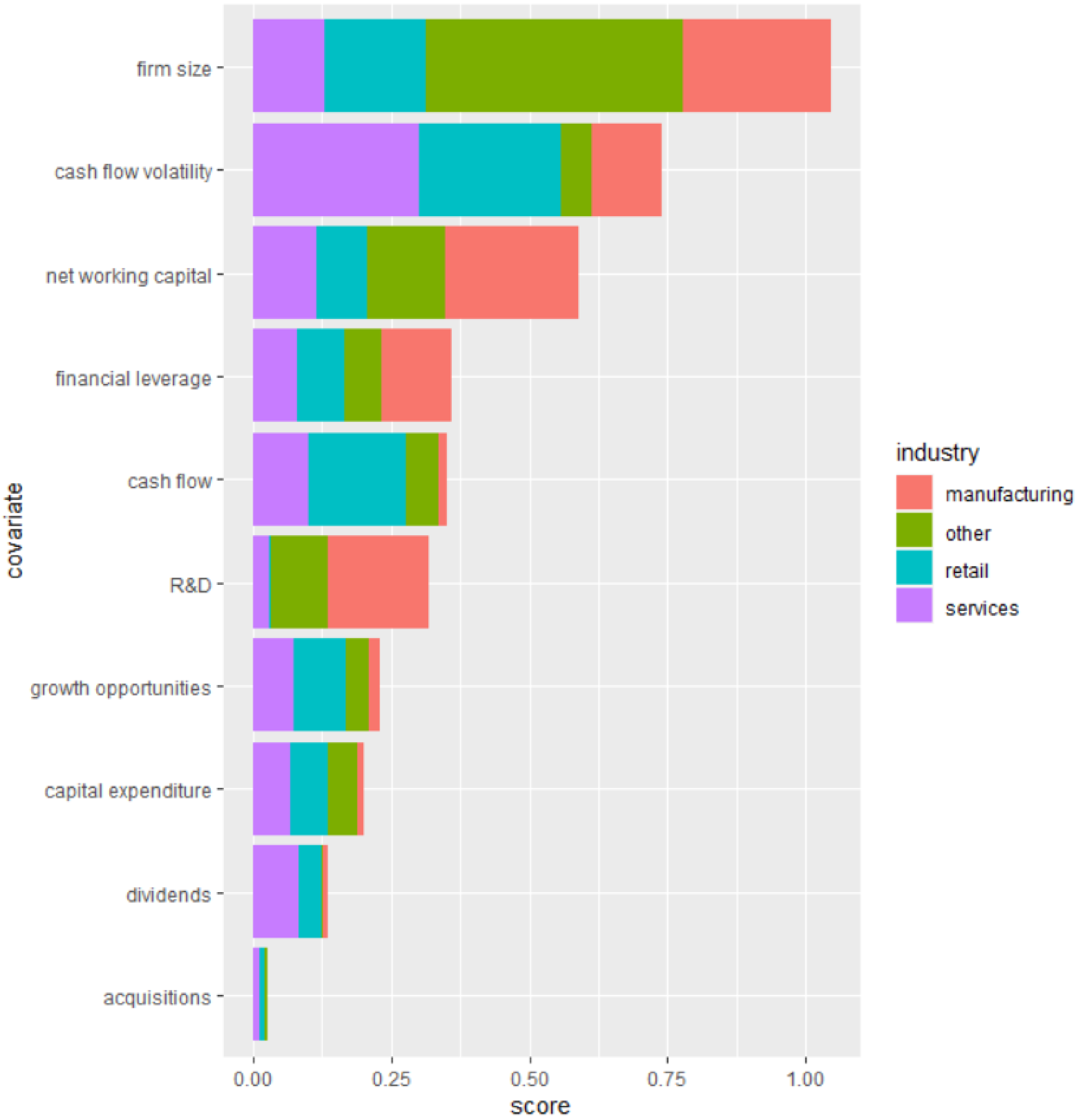
Note: This figure compares the distribution of firm-level interest rate effect estimated by the instrumental causal forest method for five-year windows (1995-1999, 2000-2004, 2005-2009, 2010-2014, and 2015-2019). Policy news shock, from Nakamura and Steinsson (2018), is used as the instrumental variable for the raw interest rate. The raw interest rate is proxied by the nominal 3-month T-bill rate. The availability of data for the shocks limits our sample to 1995-2019. We collect quarterly data from Compustat for this period and incorporate it with monetary policy shocks data.

Appendix 4.7: Heterogeneous effect of cost of carry around financial crisis



Note: This figure compares the heterogeneous effect of cost of carry pre (2003-2007) and post (2008-2012) global financial crisis of 2008.

Appendix 4.8: Variable importance ranking of covariates by industry



Note: This figure compares the importance scores of ten covariates in the trees grown by causal forest, estimated in Table 7, for four sectors: manufacturing, services, retail trade, and other industries.

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Concluding remarks

The amount of data being generated and collected is growing exponentially. High-dimensional data is common in various scientific fields. While high-dimensionality offers numerous advantages, it also presents several technical challenges. In the modern age, data is often complex and multivariate, meaning it consists of numerous variables that interact in intricate ways. Traditional statistical methods may struggle to capture these complex relationships. Machine learning (ML) techniques are designed to handle big data and extract valuable insights from it.

Specifically, ML techniques offer significant potential benefits in corporate finance, from tackling the non-normal conditions in practical applications (such as nonlinearity, collinearity, etc.) to improving the model accuracy in terms of prediction and estimation. These benefits collectively empower organizations to make more informed decisions, ultimately driving better financial outcomes. In this thesis, we employ new advancements in machine learning methods, including double machine learning (DML) and causal forest (CF), on three corporate finance issues.

In Chapter 2, we extend the application of DML technique to corporate cash literature. Although describing the surge in cash has been the subject of many studies, a major gap remains in the literature regarding the relative importance of potential drivers. In this chapter, for the first time, we try to compare the effect of selected drivers proposed in literature. Our results show that the economic importance of some of the drivers is influenced by other ones, underscoring the importance of considering the existing drivers in examining the role of a new driver in future research. Furthermore, we document that the sensitivity of cash to the drivers varies over time. Particularly, intangibles, which are of little importance at the beginning of the sample period, become more important in the following years in the era of the knowledge-based economy. In addition to academic importance, this identification has an important implication for policymakers to be aware of probably one of the most important reasons for the slow recovery from the Great Recession. Decreasing trend of tangibles in the balance sheet of the US firms and shifting towards intangibles, started from the late-1970s, requires companies to give up investment to build up precautionary savings, and hence economic growth is expected to slow. Although we try to conduct a comprehensive analysis to ranking the drivers of the cash increase phenomenon, we have no claim regarding to other drivers introduced in the literature, e.g., just-in-time inventory system adoption, revenue-expense correlation, etc.

In Chapter 3, we apply the DML technique on the M&A returns. Particularly, we exploit this method to find the most important determinant of short-term announcement returns. In fact, a great deal of effort has been made in literature to identify the determinants of merger performance. But there is still one un-answered question regarding the relative importance of these covariates. Our results suggest that only a sparse set of variables present important information in predicting M&A returns beyond the variables that consistently appear in extant empirical research. These variables, which include target's number of analyst, target advisors, and bidder advisors, are closely related to the issue of information asymmetry in M&A deals. In summary, our findings confirm the abundance of nonessential factors within M&A literature, emphasizing the need to forge novel theories for discerning potential predictors that elucidate M&A returns.

In Chapter 4, we examine the granular impact of cost of carry, as a measure of opportunity cost of holding cash, on cash holdings. For this purpose, we utilize the CF algorithm. The benefit of this method is that we are able to investigate firm-level sensitivity of cash to cost of carry instead of looking at an average estimation for the entire population. In this way, we can identify firms that react differently to interest rate changes. Our results show that the density of cost of carry effect with entirely negative values during the 1970s and 1980s have been moving into positive territory since the 1990s. This phenomenon is perhaps due to the introduction of sweep program in the middle of the 1990s. The changes made in payment methods under the influence of this technology substantially decreased the cost and time required to convert less liquid assets into cash for transaction purposes. Therefore, some firms started to manage their liquidity outside the framework set by theoretical models. We also document that firm size and net working capital are the two main sources of this heterogeneity. Particularly, we find that the effect of size on the sensitivity of cash to cost of carry is not a straightforward linear effect, as opposed in literature. Instead, the cost of carry effect changes non-monotonically with firm size.