IMPACT OF REGULATION AFTER THE FINANCIAL CRISIS

PhD. Thesis

By

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Abstract

This thesis comprises five Chapters on the impact of regulation after the crisis of 2007 in the UK and US. The analysis considered different aspects of the crisis as reflected in the three main chapters of this thesis that includes the impact of regulation on the probability of a financial crisis, The impact of regulation on systemic risk, and contagion, interdependence, and the impact of regulation. Chapter 1 introduces the main themes within the thesis. It provides an outline, scope, and brief discussion of thesis contributions.

Chapter 2 starts by providing the thesis's theoretical background after setting out key themes (e.g. early warning models, theories of regulation and banking regulation) that form the research basis. The chapter analysed the impact of regulation on the probability of a crisis, i.e. it assessed the extent that recent regulation has reduced the chances of another crisis occurring. We employ an early warning signal method – Logit model and Bayesian model average to establish this impact. Our results have shown recent regulation has reduced the probability of financial crisis both in the UK and the US and concluded with the proposal of adding Basel III liquidity thresholds variables to the 'early warning signal' literature.

Chapter 3 examines the interaction between systemic risk and bank-level variables that were the target of regulation after the crisis. The analysis shows the level of impact that some of the Basel III (an international regulation) and other national regulations (e.g. Ring Fencing in the UK) are

having on systemic risk. We employed ΔCoVaR as the proxy for systemic risk and estimated CoVaR using quantile regression and the Garch model before applying Kupiec (1995), Christoffersen and Pelletier (2004), and Lopez (1999) tests to establish the accuracy of our results. Our result shows that the variables that capture Basel III regulation have a significant impact in reducing systemic risk. In contrast, UK-specific regulation indicates little to no impact in reducing systemic risk. Chapter 4 investigate the impact regulation has had on CDS indexes. In so doing, we established the existence of contagion before the implementation of regulation and Interdependence after that. We then employed Regime dependent Impulse Response Functions to show the indexes that react most to shocks from the system. Finally, chapter 5 concludes and summarises the thesis and provides a discussion of policy implications.

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Declaration of Originality

I herewith declare that this thesis is my work. All material and sources that do not constitute my work have been explicitly acknowledged and referenced. This thesis is a record of the original work carried out by myself under the supervision of Professor Georgios Sermpinis and Doctor Charalampos Stasinakis at the University of Glasgow, United Kingdom. The copyright of this research belongs to the author under the terms of the United Kingdom copyright acts. The due acknowledgement must always be made to use any material contained in or derived from this thesis. The thesis has not been presented elsewhere in consideration for a higher degree.

Muhammed Shamsuddeen Adamu.

Dedication

This work is dedicated to my family: Bariatu Dikko and Zainab Zainu (my late mothers), Bappa, Abdul-Rahman, Ameerah, Khalifah, Sha'awa and Muhammad (my siblings) and the two people who started me on this journey: Mal. Idris and Jibril Adamu. Khadijah Green (whom there will never be any like) and Maryam-Hanifah (whose arrival pushed me finish this work). The unparalleled love, support and patience they provided throughout my existence cannot be over emphasized.

“to restrain private people, it may be said, from receiving in payment the promissory notes of a banker, for any sum whether great or small, when they themselves are willing to receive them, or to restrain a banker from issuing such notes, when all his neighbors’ are willing to accept of them, is a manifest violation of that natural liberty which it is the proper business of law not to infringe, but to support. Such regulations may, no doubt, be considered as in some respects a violation of natural liberty. But those exertions of the natural liberty of a few individuals, which might endanger the security of the whole society, are, and ought to be, restrained by the laws of all governments, of the most free as well as of the most despotical. The obligation of building party walls, in order to prevent the communication of fire, is a violation of natural liberty exactly of the same kind with the regulations of the banking trade which are here proposed” —Adam Smith.

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Chapter 1

Introduction

1.1 General Background

The crisis of 2007 and the implementation of new regulation soon afterwards is not particularly an isolated case in history[1]. The frequency of crisis will suggest sufficient economic understanding and solutions. However, this is not empirically the case. Therefore emphasising the need to understand the nature of the economic/financial crisis with its associated response overtime. Hence, the questions that remain are; what is the right type of regulation? Should there be a regulatory response from the government at all? Does regulation have any meaningful impact? This thesis serves as a contribution to answering some of these questions.

[1] Recent financial history has shown between 1976 to 2007 there has been around 147 systemic banking crisis across the world Laeven, L. & Valencia, F. 2012. Systemic banking crises database: An update.

As pointed by Alan Greenspan in 1997, ”It is critically important to recognize that no market is ever truly unregulated. The self-interest of market participants generates private market regulation. Thus, the real question is not whether a market should be regulated, rather the real question is whether government intervention strengthens or weakens private regulation” (Born, 2011). This follows the “capture” theory of regulation that suggests as a rule, regulation is acquired by the industry and is designed and operated primarily for its benefit (Stigler, 1971). Contrasting argument is the Public interest theory of regulation that suggests; regulation is supplied in response to demand by the public to correct inefficient and inequitable market practices (Ugochukwu Uche, 2001). As echoed by Michel (1998), Capital itself has no inherent capacity for producing positive effects only (given its unbounded ability to accumulate more), and if left unchecked it can lead to concentration of wealth in the hands of a few at a cost to the society. Highlighting regulation as a necessary part of creating a fair society.

Understanding the proponents of regulation’s arguments also requires restating traditional economic theory that suggests there are three primary purposes of regulation. These are; 1. To constrain the use of monopoly power and the prevention of serious distortions to competition and the maintenance of market integrity 2. To protect the essential needs of ordinary people in cases where information is hard or costly to obtain, and mistakes could devastate welfare and 3. To shield, where there are sufficient externalities that the social, and overall costs of market failure exceed both the private costs of failure and the extra costs of regulation. It[2] also highlights a lack of sufficient macro objectives that is more relevant to the current global nature of economics/finance. The combination of these and the reality of new set of regulations also justifies empirical analysis on the impact recent regulation.

The Turner (2009) review highlights that the crisis has raised important questions about the intellectual assumptions on which previous regulatory approaches have largely been built upon. The review shows that part of regulation's theoretical challenges lie within the neo-classical economic theory that states financial markets can be both efficient and rational. Using this, the regulatory approach to financial market becomes removing the impediments that produce inefficient and illiquid markets as vast amount of literature has shown that share prices in well-regulated liquid markets, follow 'random walks'[3]. Therefore, with rational market participants, prices tend towards rational equilibrium. The implication for regulatory approach is that: market prices are good indicators of rationally evaluated economic value. However, there has always been scepticism about this idea.

The general theory of employment (Keynes, 1937) suggested that equity prices are not necessarily driven by rational assessment of available in-

[2] Economic theory of regulation.

[3] Note that the finding of 'random walks' (i.e. the nonexistence of chartist patterns) does not imply that the determinants of the price movements are random and irrational, but rather that they are determined by flows of relevant information which, since they arise in a fashion unrelated to past price movements, will result in apparently random but in fact entirely rational price movements.

formation [4]. Minsky (1986) argues that financial markets and systems are inherently susceptible to speculative booms which, if long lasting, will inevitably end in crisis. Again, The Turner (2009) review asserts that financial market theory in the last 20 to 30 years suggests (i) efficient and liquid financial markets deliver significant allocative efficiency benefits by making possible a full range of contracts. Thus, enabling providers and users of funds to more effectively meets their risk preferences, return and liquidity. (ii) Markets are sufficiently rationale to justify a strong presumption favouring market deregulation and (iii) that even if markets are theoretically capable of irrational behaviour, policymakers will never be able to judge when and how far they are irrational with sufficient confidence to justify market intervention.

This idea that suggests deregulation is further supported by Friedman and Schwartz (1986). They examine the inflationary surge in the U.S. between 1960s and 1970s, and suggested the poor performance of the monetary authorities reinforce the conclusion that leaving monetary and banking arrangements to the market would have produced a more satisfactory outcome than was actually achieved through governmental involvement. They concluded that government failure might be worse than market failure.

[4] Keynes likened investing in financial instruments to 'those newspaper competitions in which the competitors have to pick out the six prettiest faces from 100 photographs, the prize being awarded to the competitor whose choice most nearly corresponds to the average preferences of the competitors as a whole; so that each competitor has to pick not those faces which he himself finds prettiest, but those which he thinks likeliest to catch the fancy of the other competitors, all of whom are looking at the problem from the same point of view. It is not a case of choosing those which to the best of one's judgment are really the prettiest, nor even those which average opinion genuinely thinks the prettiest. We have reached the third degree where we devote our intelligence to anticipating what average opinion expects the average opinion to be. And there are some, I believe, who practice the fourth, fifth and higher degrees'

Such an understanding ushered the era of "de-regulation" in the 1970's after much of the regulations of 1930's. This might suggest the public theory of regulation argument as weak, since deregulation has proved generally beneficial in many sectors of the economy (Greenspan, 2005, Robson, 1998, Winston, 1998). However, The Turner (2009) report assessed the efficient and rational markets assumptions and concluded that; empirically and theoretically the theory is either inconclusive or lacks a significant ability the fit with reality.

Within this framework, our approach is empirical. We argue here that regulation or deregulation would not necessarily produce the optimal outcome. That is, in the absence of a regulatory authority that understands the changing phases of the business environment and implement the right type and level of regulation/deregulation that reduces risk, improve economic development without hampering innovation, provides growth and incentives for the right type and amount of risk that businesses are ready to take; theoretical arguments will remain inconclusive. We therefore statistically analyse some of the recent regulations implemented after the financial crisis of 2007 in answering the question; has regulation made an impact after the crisis? Our study recognises that there are several dimensions to the crisis and different regulations aimed at the multi-faceted parts of the crisis. Therefore, our analysis (within this and other chapters) covers the impact of regulation on crisis probability, systemic risk and contagion.

Considering the impact of the crisis globally, the US/UK suffered the effects of the crisis the most. However, they applied relatively different types of regulation. There was also an international response to the crisis (Basel III) that both adopted with subtle differences—making it important to establish the impact these regulations have on the common crisis phenomena of the probability of a crisis, systemic risk, contagion and interdependence in both countries.

Overall, the thesis objective is to provide answers to the questions; has Basel III (the international regulatory response) impacted the probability of another crisis happening again? Was there evidence of systemic risk? Has regulation reduced systemic risk? Was there a contagion? Through which channels did contagion spread? Has regulation changed contagion effects to interdependence? To answer these questions, we applied statistical methodologies base on the theoretical underpinning of (i) Probability of crisis using Bayesian model average and Logit model (ii) Systemic risk using Conditional Value at Risk and Garch models, and (iii) Contagion/Interdependence using Markov Switching Value at Risk and Garch models. Our models prove robustly sufficient in capturing the impact of regulatory changes impact on mentioned crisis phenomena highlighted.

1.2 Thesis outline

This thesis consists of three main chapters, which are independent but closely related. The central theme that runs through all chapters is the impact of regulation after the crisis. We analysed crisis from three main features, i.e. crisis probability, Systemic risk and contagion. The concept of the probability of a crisis is closely related to systemic risk. That is, the crisis only burst after the existence of systemic risk. In the same light systemic risk occurs due to the high level of interdependence that turns into contagion. The subtle but important difference between these concepts meant that we had to use different models in each chapter to effectively capture the impact of regulation. In addition, we use the appropriate variables in each chapter that regulation affected in order to capture each stylised impact that provides a fairly holistic understanding of the regulations implemented in the UK and US.

1.2.1 Chapter Two: Scope and Contribution

This chapter examines the impact of recent regulation in mitigating the probability of financial crises. We employ an early warning signal method – The logit model to show this relationship. Furthermore, we apply the Bayesian model average for robustness checks. This is similar to Barrell et al. (2009) and Davis and Karim (2008). However, we contributed by sampling our data to reflect changes in regulation and, therefore, its impact. We also use empirical Basel III data as opposed to assumed increases to

Basel III threshold in previous literature. Thus, allowing us to establish the Basel III variable as part of an early warning system model.

1.2.2 Chapter Three: Scope and Contribution

Using quarterly delta conditional value at risk (ΔCoVaR; a proxy for systemic risk) from 2000-Q1 – 2019-Q4, with bank-level panel-data, we analyse the impact of regulation after the financial crisis of 2007 on systemic risk in the UK financial system. We estimated CoVaR using quantile regression and the Garch model before applying Kupiec (1995), Christoffersen and Pelletier (2004), and Lopez (1999) tests to establish the accuracy of our results. Our result shows that the variables that capture Basel III regulation have a significant impact in reducing systemic risk, while UK specific regulation shows little to no impact in reducing systemic risk.

Our main contribution to the literature is analysing the impact of regulation using our systemic risk measure (ΔCoVaR) against bank-level targeted variables. Our second contribution relates to the analysis of systemic risk. Previous pieces of literature (e.g. Girardi and Ergün, 2013, Huang et al., 2012a, Tobias and Brunnermeier, 2016) have used both models (i.e. CoVaR and Garch) as applied here when estimating systemic risk. However, what we have added is the application of accuracy tests to show the model that is more accurate when estimating systemic risk (on bank regulatory variables). This study also considers variables that were either newly introduced (such as ring-fencing) or those that are calculated differently (e.g. leverage ratio, regulatory capital) because of changes in the regulation. Therefore, providing a clear understanding of the impact, these policies have created on systemic risk.

1.2.3 Chapter Four: Scope and Contribution

Using a Markov Switching VAR, we investigate the impact regulation has had on CDS indexes in the US and UK. In so doing, we were able to show the existence of contagion prior to the implementation of regulation and Interdependence thereafter. We then employed Regime dependent Impulse Response Functions to show the indexes that react most to shocks from the system. We also applied DCC-GARCH to check the robustness of our results.

This chapter's first and main contribution is the impact regulation has had on credit default swap indexes in reducing contagion. The second contribution of this analysis establishes (using credit default swap spread), if there was contagion or interdependency within sectors of the economy in the US and the UK during the crisis and if this has changed after introducing regulation. The third contribution shows through which channel contagion occurred. That is, which CDS index contributed to the propagation of risk within the economy through the application of Impulse Response Functions (IRF's).

Chapter 2

Impact of Regulation on the Probability of Financial Crisis

2.1 Abstract

This study examines the impact of recent regulation in mitigating the probability of financial crises. We employ an established early warning signal method – The logit model to show this relationship. Furthermore, we apply the Bayesian model average (BMA) for robustness checks. Recent financial history has shown between 1976 to 2007, there have been around 147 systemic banking crises across the world (Laeven and Valencia, 2012). This figure is exclusive of other types of crisis like debt, inflationary, sovereign types of crisis.

Using the logit model, we ran seven regressions to capture the regulation's impact on another crisis probability. Using a sample of lagged variables to

avoid the endogenous effect, our data from 1970 to 2009 captures the relationship between crisis probability and explanatory variables. Data from 2010 to 2018 highlights the change in the relationship due to new regulations. Our results show an inverse relationship between real economic growth and the probability of a crisis occurring and a positive relationship between an increase in house prices and crisis probability. This follows the theoretical relationship assumptions between the existence of bubbles and these variables. Equally, the Basel leverage ratio behaves inversely to crisis probability, as shown further in the analysis, while traditional bank leverage (debt to equity ratio) has a positive relationship. The study shows that at a 10% level of significance, the interest rate is significant in explaining the crisis. This is similar to Demirguc-Kunt and Detragiache (2005) 's work, where they found that crisis occurred in periods of low GDP growth and high interest rates. Our BMA results show that the estimates from Basel III thresholds are robust.

Furthermore, margins analysis that allows us directly infer from regression coefficients showed Bank liquidity ratio to reduce the crisis ratio by 1.5% over the period, while the Bank leverage ratio increased the crisis probability by 5.7%. The capital adequacy ratio minimises the probability of crisis by about 2.4%.

2.2 Introduction

An Economic crisis is arguably the next most disruptive challenge that nations continue to face after a security crisis. The literature (e.g. Barrell et al., 2010b, Barrell et al., 2010a, Davis and Karim, 2008, Laeven et al., 2016, Laeven and Valencia, 2018, Duffie, 2017) suggests different factors such as derivatives, moral hazard, shadow banking activities, information asymmetry, credit ratings, GDP, credit/liquidity, high leverage to have caused the crisis of 2007. While any of these variables or all of them may have contributed, there is a synonymous agreement that lack of proper regulation that reflects the changing climate within the financial and banking sector has contributed to the occurrence of the crisis (Turner, 2009). This led to regulations that deal with the crisis as it happened and put in place long-term measures that can reduce the probability of a crisis occurring moving forward.

The definition and understanding of systemic banking crisis, its severity, its onset, and its duration is a matter of judgement and debate (Demirgüç-Kunt and Detragiache, 1998). Therefore the definition that serves the purpose of this analysis is the one given by Cashin and Duttagupta (2008). They defined a systemic banking crisis as an episode involving banking sector problems that resulted in; exhaustion of much of the capital and closure, mergers, large-scale nationalisation of banks, extensive bank runs; or large-scale liquidity support by the central bank to avoid a run on deposit institutions.

Understanding the recent crisis and regulations taken is essential to the smooth functioning of the financial sector and the whole economy. It is even more critical when we consider the number of times crisis have occurred and their associated cost. Furthermore, every time a crisis of this nature has happened in the past, it was not the case that there were no regulations at the time. Therefore, it is imperative to understand the theories that inform these regulations, the nature and justifications of the regulations, how they have functioned in the past to inform academic discourse and policymakers.

Studies within the early warning signal literature focus on establishing the variables that can serve as signals for a looming crisis to policymakers. The importance of such studies is apparent. However, the focus here goes beyond such, even though the analysis does provide such contribution. The focus here is establishing the impact regulation has had on crisis probability. While many countries have put different regulations in place to safeguard the banking system further, this chapter is looking at some part of the Basel III regulation. In particular, we analyse the impact of the new Capital adequacy ratio, Leverage ratio and Liquidity ratio on crisis probability. Although Basel III has made significant progress in tackling issues beyond its traditional scope of monetary/capital thresholds, these thresholds remain the cornerstone of Basel regulation. Therefore, we are focusing on these thresholds and their impact on reducing the probability of crisis going forward.

The literature concerning measuring causes of crisis can be attributed to the seminal work of Demirgüç-Kunt and Detragiache (1998), where they measured the variables that had an impact on the probability of a crisis occurring. This chapter's major contribution is establishing the impact of regulation (Basel III) on the probability of a crisis. Another contribution is it established the relationship between the new Basel III leverage ratio and crisis probability, We also applied margins analysis to further establish the impact of regulation on crisis probability and the inclusion of Basel III liquidity thresholds to EWS literature. Unlike other related literature, e.g. Barrell et al. (2009) and Davis and Karim (2008), where assumed liquidity requirement impact was undertaken, this chapter uses regulatory data to establish the impact on crisis probability. This chapter also analyses a two-sample period to show the impact regulation has had on crisis probability that is not in previous studies.

We use the work of Laeven and Valencia (2010) to justify our choice of sampled nations. They showed the UK and US to be the only countries in the 2007 - 2008 crisis to have experienced the extreme form of systemic banking crises. This is a situation where both countries experienced all five conditions of 1. Banking extensive liquidity support, 2. Direct bank restructuring costs, 3. Asset purchase outlays, 4. Guarantees on liabilities, and 5. Bank nationalisations.

A systemic banking crisis requires only any three of these to exist. These countries consistently ranked amongst the highest to have experienced the effect of the crisis in market capitalisation, fiscal cost, increase in public debt, and output loss. They also have put regulations in place soon afterwards as much or more than most countries that experienced a systemic crisis. These reasons provide the justification and the rationale why the focus of the analysis is on limited to these two countries.

There is an implicit assumption here that suggests; recent regulations intend to bring about stability that reduces crisis probability. The analysis starts by providing the intuition behind using early warning signal methods to measure crisis alongside the literature review. To properly position this research within the literature, a summary of regulatory theories is provided along with justification for the existence of financial intermediation and its regulation. This forms the basis for the regulation of the financial sector after the crisis of 2007, where an overview of Basel and detailed discussion of Basel III is undertaken. The rationale for the data sets used within the analysis is provided, alongside definitions of our dependent and explanatory variables. To measure the regulatory impact on crisis probability, we apply the Logit model together with the Bayesian model Average for robustness check. Results of the analysis are then provided. Finally, a conclusion that shows the relationship and impact of regulation on crisis probability is drawn.

This chapter proceeds as follows. Section 2.1 to Section 2.2.1 provides an examination of early warning signal literature, regulation and the importance of Banks. Section 2.3 to Section 2.3.2 provides an overview of the regulation after the 2007 crisis, Basel and detailed Basel III. Section 2.4 looks at methodology literature. Section 2.5 Describes the data used for the analysis. Section 2.6 Is the methodology discussion, and Section 2.7 and 2.8 is the presentation, interpretation of results and conclusion, respectively.

2.3 Literature Review

2.3.1 Early Warning Models

Barrell et al. (2009) used a logit model to estimate the net benefit of tighter bank regulation in the UK with respect to assumed increase in banks' capital and liquidity ratios. Their model showed an increase in these ratios by 1 percent would likely reduce crisis probability by about 6 percent. The work of Demirgüç-Kunt and Detragiache (1998) is one of the earliest and most frequently cited literature concerning 'Early Warning Signal' to model crisis probability (de-Ramon et al., 2012). They used a multivariate panel logit model to show what variables were significant to crisis probability and to what extent these variables played a role in determining the crisis across different countries. As used by Davis and Karim (2008) and Barrell et al. (2009), their model's variant forms the starting point for the analysis here. Demyanyk and Hasan (2010) analysed methodologies used to examine banking/financial crisis. They showed that intelligence-modelling techniques such as support vector machine-neutral network have helped shed light on the fuzzy clustering and self-reorganising classification tools used to identify potentially failing banks. Whereas, for regulatory purposes, the use of the logit method is more frequently used for modelling, signalling and crisis prediction purposes.

Caggiano et al. (2016) also mentioned that the recent global financial crisis has stimulated a new wave of policy and academic research aimed at developing empirical models. They reviewed EWS as used by Demirgüç-Kunt and Detragiache, 2005; Babecký et al., 2013; and Kauko, 2014. . Showing the EWS for systemic banking crises has come up with two dominant analytical techniques for predicting signs of banking distress, namely the signals approach and the binomial multivariate logit framework. The signals approach, first developed by Kaminsky and Reinhart (1999) and adopted, among others, by Borio and Lowe (2002); Borio and Drehmann (2009) and Drehmann and Juselius (2014), considers the impact of covariates in isolation and benchmarked against specific threshold values. The fluctuation of covariates beyond a threshold level chosen to minimise the noise-to-signal ratio suggests a threat to financial stability. However, binomial multivariate logit as used by Demirgüç-Kunt and Detragiache (2000); Davis and Karim (2008a, 2008b) and Alessi et al. (2015) amongst others, shows that; crisis probabilities estimated through the binomial multivariate logit exhibit lower type I (missed crises) and type II (false alarms) errors than the signals approach, and therefore provide a more accurate basis for building an EWS. This is despite recent attempts to integrate the two approaches to analyse interaction effects of macro-financial variables through, for example, the use of the binary classification tree technique (Davis and Karim, 2008b).

2.3.2 Theories of Regulation

While an agreement is absent when it comes to the exact definition of the term regulation, Koop and Lodge (2017) adopt the definition provided by Selznick (1985), of regulation being a “sustained and focused control exercised by a public agency over activities that are valued by the community”. And that of Black (2002), as regulation being “the sustained and focused attempt to alter the behaviour of others according to defined standards and purposes with the intention of producing a broadly identified outcome or outcomes, which may involve mechanisms of standard-setting, information-gathering and behaviour modification”. These Captures the essence of the various definition of the term regulation within social sciences without delving into extensive details of differing opinions.

Michel (1998) also stated, ‘regulation theory is concerned with heterogeneous economic processes in which necessity and contingency, the constraint of the past and the creation of the new are intertwined. It deals with processes that emerge, are reproduced, and then wither away under the effects of the unequal development inherent in capitalism’. He went on to suggest that given the potent nature of capital, along with its ability to produce great good, also comes the capacity for creating negative impact. Capital itself has no inherent capacity for producing positive effects only (given its unbounded ability to accumulate more), and if left unchecked, it can lead to the concentration of wealth in the hands of a few at a cost to the society as was the case during the proletarian period. He concludes

that the extent to which capital can be steered for productive purposes lies within societal constructs and organisations that reflect societal values at any time.
This suggests that regulation needs to be dynamic, alongside changes within the financial system, innovations and society as a whole. Although this is not suggesting regulation is not without a cost or is necessary a more efficient alternative. The consensus that absence or poor regulation contributed to the recent crisis of 2007 does not take away the reality that even at the time of the crisis, the financial industry has regulation in place. The understanding at this point is that the problem was not the absence of regulation in itself. But regulations that were not reflective of the changes that occurred within the financial system at the time or even more to that is the possibility of regulation based on theories that do not reflect economic realities of the time. Forcing us to now question and have a more critical look at both nature and economic theories used to inform regulation before the crises.

Ugochukwu Uche (2001) Shows that there are two main conflicting theories of regulation that are commonly used to explain the origin, rationale and practice of regulation. These are the Public interest and Capture theories of regulation. The former is based on the understanding that; regulation is supplied in response to demand by the public to correct inefficient and in-equitable market practices. The argument here is that this view holds given the historical cases that it can reasonably explain. The establishment of the Securities and Exchange Commission is an example of a crisis-driven regulation in the US. An example of crisis-inspired legislation in the UK includes the Royal Exchange and London Assurance Corporations Act (Bubble Act) of 1719.

On the other hand, there will always be a cost to the provision of data and information. Therefore, the idea of the government acting as a costless and reliable body to alter markets have not been without questions. Other costs of regulation raised include the impact it can have on management style, firms' flexibility to change the business environment, etc. These issues led some to go as far as stating that the cost of regulation outweighs any benefit to correcting market inefficiencies in a market-based allocation of wealth.

Den Hertog (2010) summarises that the public interest theory of regulation assumes the occurrence of comparative analysis of institutions for efficient resource allocation of scarce resources in the economy. This theory is mainly based on the premise of prevalent market failures, the existence of an efficient political process, efficient regulatory institutions, and benevolent regulators, i.e. the absence of cost to provide regulation. Such a premise has not always been empirically the case. This idea lends support to Stigler (1971), who asserted that 'as a rule, regulation is acquired by the industry and is designed and operated primarily for its benefit'. This understanding is the general idea of the proposition termed as 'Capture theory' of regulation. This comes from the understanding that regulation is sought-after by special interest groups, and regulatory agencies are captured to influence and enact such regulations to protect the interest of the few but powerful groups. Other explanations to capture theory also include that; instead of focusing on correcting market inefficiencies, regulation focused on affecting wealth transfers in favour of industries in exchange for political support.

Generally, both theories agree that economic regulation should aim to counter the negative effect of market imperfections arising from the negative consequences of dominant firm effects, market abuse, information asymmetry and instability in other market processes. In the light of the different perspectives above, recent regulations, including Basel III, are more closely in line with public interest theory.

2.3.3 Importance of Banks and their Regulation

Although banking is a private business that aims at increasing investors profits, they play a significant and central role within any economy that sets them apart from other private businesses due to the nature and functions of the activities[1] they undertake. Freixas and Santomero (2003) concludes that to gain a good understanding of banking regulation, such analysis needs to understand why all forms of financial intermediaries exist and apply such implications to banking in order to understand its regulation, as carried out by Bhattacharya et. al (1998).

Fama (1980) argues that banks exist due to the economies of scope that exist between transferring claims on property and offering investment opportunities, while Santomero (1984) provided an explanation for bank existence using the transaction cost theory[2], which he viewed to be more relevant to financial intermediation as opposed to traditional explanations offered. Furthermore, Boot and Thakor (1993) showed that another rationale for banks' existence is the service of monitoring loans after borrowing funds to customers that they provide. In comparison, Diamond and Dybvig (1983) perspective suggests that agents face uncertainty on their consumption timing; therefore, they are better off in a banking contract that allows for some ex-ante insurance than buying financial securities.

[1] This analysis does not make a clear distinction between financial markets, shadow banking and traditional banking (even though it exist) activities due to developments that have caused the distinctions for the purposes of regulatory analysis to blur overtime as it shall be made clear later. Hence, they would be referred to interchangeably.

[2] Financial Intermediaries are facilitators of risk transfer and deal with the increasingly complex maze of financial instruments and markets.

A recent explanation of financial intermediation assumes some information imperfection in the market that makes it possible for intermediation to exist. Most of these theories argue that financial intermediaries develop endogenously due to different types of information asymmetries in order to improve the imperfection that exists within financial markets, which means that financial institutions exploit markets for their own economic gains. In other words, financial intermediation mainly arises where conditions proposed by Modigliani Miller theorem (the absence of taxes, bankruptcy costs, agency costs, and asymmetric information within an efficient market) do not exist (which is most of the reality of the financial sector). If this is correct, then it becomes rational for a government to react with regulations to correct such imperfections (even though, on occasions, these interventions are not always the optimal resolution). Hence, the reality of imperfect markets, as described above, justifies the existence of regulation. This again confirms the understanding of regulation from a public interest theory perspective.

Schumpeter (1934) analysed money creation through credit as the fundamental function via which banks make it possible for entrepreneurs to adopt new factor combinations. New bank money consists of claims on services and goods yet to be produced by the economy. These functions, taken altogether, make the banking sector a very sensitive and important part of the economy and society that justifiably need to be supported to function as efficiently as it can be possibly achieved. The consequences of bank failures or crisis has overtime established how vital this industry is to a well-functioning economy, given the spillover effect it has at a micro and macro level, and recently global impact. This concern underscores the contagion impact from the banking sector onto the real economy and establishes reasons for bank regulation. Where it not for this contagion effect, then there might be no reason for standard or minimum requirements set within the industry. However, issues like the protection of depositors' wealth is yet another reason why regulation might be necessary.

2.3.4 Regulation after Financial Crisis of 2007 – 2009

Brunnermeier et al. (2009) pointed out that although there exists a body of financial regulation already in existence (when the 2007 crisis occurred). They argue; these regulations are usually incremental in nature and often brought about because of a loophole that became apparent within the system due to fraud or crisis. This can be historically traced to the most important regulations of the past, such as the crisis of the 1930s that brought about Glass-Steagall and Deposit Insurance, Basel I, after a local bank crisis in Germany and Sarbanes-Oxley after the Enron fraud.

A rational assumption is that regulators and regulatory agencies have taken steps to better understand all factors stated to have contributed to the crisis, such as; low liquidity as compared to the risk undertaken and use such information to guide the new framework of regulations now in place. The focus of this analysis[3] would be on the United States and the United Kingdom for the reasons earlier stated. While both these countries have specific regulatory changes in place, what is shared between both is the new Basel III framework.

[3] This chapter will only focus on Basel III, and other regulations that are particular to the US and UK (Dodd-Frank Act and Ring-Fencing respectively) will be briefly highlighted here and analyzed in subsequent chapters. Note Basel III is still with respect to UK and US only.

2.3.5 Basel Accord

King and Tarbert (2011) concluded that Basel III is without a doubt a direct response to the 2007 crises, just like what happened in 1974 when apparent issues with international banks lead to the creation of the Basel I accord. For comprehensiveness, before looking at Basel III, a general outline of the Basel overview should be understood at this point.

From a generic and historical point of view, banking is a business involved with leverage. It is a situation where companies (banks) borrow/receive money from the surplus and lend it to the economy's deficit sectors (at least in theory). There is an inherent assumption within this model that banks can get back their loans, make profits and pay back depositor. In practice, the amount banks lend out mostly exceeds its deposits, therefore creating a mismatch. This mismatch has the capacity of a ruinous impact on banks and the economy at large. Hence, the rationale for liquidity or bank capital regulation is to provide a cushion against such mismatches that comes with high cost.

Consequently, in 1974, the Basel Committee on Banking Supervision (BCBS) was formed to advise national financial regulators on a common capital requirement for internationally active banks. There was also a perceived failing of deregulation around the time that further informed the Basel committee's need. Part of this was that deregulation allowed internationally active banks to take advantage of differences in national treatment of similar assets for capital requirement purposes. Deregulation also made it possible for national standards not to always link capital requirements to actual risk levels, i.e. not taking into account exposures beyond those reflected within the four corners of the balance sheet. Consequently, a regulatory consensus started to build around a set of global standards that would provide guidance on internationally active banks' proper capital levels. The result was Basel I accord in 1988.

By the late 1990s, it became apparent that the regulatory standard, as set out by Basel I accord, was not sufficient to overcome the continued crisis that marred the banking system. Therefore, the Basel Committee, seeking to offer a more comprehensive and risk-sensitive approach to capital regulation, formally adopted the new framework of Basel II in 2004. Basel II involved three so-called "pillars": minimum capital requirements, the supervisory review process, and market discipline. Basel II's significant contribution was its wholesale revision of Basel I's rudimentary "bucket" approach to Risk-Weighted Assets (RWAs).

However, the recent financial crises have proved again that the standards set by Basel II (even with an emphasis on risk assessment models) are not sufficient in several areas. For example, Banks were able to take advantage of the rather loose definition of Tier 1 capital (left largely intact from Basel I) by structuring financial products that enabled them to comply with Basel II at a lower cost of capital. Likewise, banks managed to structure their liabilities in a manner that the accord failed to capture. They were able to keep capital requirements for trading book assets and securitisations under Basel II comparatively low, especially when compared to assets registered on the banking books. Equally, the financial crisis revealed critical flaws in the risk management models used by the majority of banks, especially the famous 'Value at Risk' model that is criticised for being backward-looking and unable to capture risk as presumed. The crisis also showed the inadequacy of credit rating agencies and raised questions about their credibility. Another flaw of Basel II, even according to the Basel Committee, was the "failure to capture major on- and off-balance sheet risks, as well as related derivatives exposures".

2.3.6 Basel III

Basel III's central focus is on increasing the quality and quantity of capital banks must hold. Alongside this is an extensive reassessment of risk coverage guidelines and the creation of a set of system-wide macro-prudential measures. Basel III introduces a set of tools and standards at the macro-prudential level, such as; a countercyclical buffer and a universal leverage ratio. This is to address systemic risk within the global financial system. On its face, Basel III maintains the requirement that a bank's "Total Capital" must be at least 8 per cent of RWAs as was set by Basel I and remained essentially unchanged in Basel II. However, Basel III requires that at least 75 per cent of a bank's Total Capital consist of Tier 1 capital, with only up to 25 per cent of Total Capital consisting of Tier 2 capital.

Tier 1, also referred to as 'going concern' capital, is to provide the bank a secure equity cushion, while Tier 2 capital, also referred to as 'gone-concern' is to serve in providing sufficient loss absorption capital in periods of insolvency. Furthermore, Basel III has two additional capital buffers intended to serve as further defences against future losses: a capital conservation buffer and a countercyclical buffer. The common principle underlying both buffers is that banks should build up pools of capital during "good times," i.e. periods of strong growth that can be used during the inevitable "bad times" when unexpected losses may occur. Basel III requirement also pointed out the flaw with the notion of capital requirements solely based on RWAs. Before the crisis, several banks and other financial institutions built up leverage that was seen as excessive while still showing strong capital ratios as measured against RWAs. Hence, a "leverage ratio" is introduced to overcome this challenge. Its calculation is made by comparing Tier 1 capital with "total exposure" without reference to RWAs. The overall target is a leverage ratio of at least 3 per cent (i.e. Tier 1 capital should be at least three per cent of total exposure).

Acharya (2012) explained that the purpose of the Basel accords was to provide a common risk-based assessment for bank assets and required capital levels. To achieve this, Basel III categorised risks into two parts that can cause a financial firm to fail. First is solvency or capital risk. This is where the market value of the firm's assets falls below its obligations. Second is liquidity risk, where the firm cannot convert assets into cash to pay off its obligations because asset markets have become illiquid. Stated differently is where the firm is unable to roll over its maturing debt obligations with immediacy to some point in the future.

He further highlighted that; there is still no focus on measuring quantities that actually reflect systemic risk, such as; the change in the value of a financial firm's assets given a macroeconomic shock and the impact such a shock has on its liability and funding structure. In the same vein, whatever capital and/or liquidity requirements are placed on banks, it is highly likely that the financial activities affected by these requirements will just move elsewhere in the shadow banking system. That is, without the understanding that the complete financial system must have unison treatment, Basel

III will run into the same shadow banking issues that arose with Basel I and II. Therefore, underscoring the importance of this analysis.

With another look into the accord, Hannoun (2010) states that Basel III has substantially improved the coverage of risks in areas related to leverage ratio that provides the benefit of safeguarding against risk and any attempts to circumvent the risk-based capital requirements. It (leverage ratio) achieves this by measuring the bank's Tier 1 capital as a % of its assets plus off-balance sheet exposures and derivatives. Finally, While some in the financial community are sceptical about the usefulness of a leverage ratio, the Basel Committee's Top-down Capital Calibration Group recently completed a study that showed that the leverage ratio did the best job of differentiating between banks that ultimately required taxpayer support in the recent crisis and those that did not.

Table 2.1: BASEL III Capital Adequacy Standards

CAPITAL TYPE	Year to Regulation Adherence 2013	2019
Minimum equity capital ratio (pure stock)	3.5% of RWAs	4.5% of RWAs
Minimum tier-1 capital	4.5% of RWAs	6.0% of RWAs
Minimum total capital (plus new capital conservation buffer)	8.0% of RWAs	10.5% of RWAs

Notes: source Bank for International Settlements. 2010(b). Group of Governors and Heads of Supervision announces higher global minimum capital standards, Annex 2 (press release). Basel, Switzerland.

While Basel III has been broadly accepted as a right step concerning Capital regulation, Acharya (2012) showed some fundamental issues surrounding it, especially with respect to the recent crisis. He highlighted how the idea of risk-weighted assets (RWAs) has conceptual flaws as a macro-prudential tool. That is to say, while macro-prudential regulation is concerned with system-wide risk, Basel capital regulation is concerned with individual firm risk. This idea of individual risk has the potential of increasing system risk, in the sense that these institutions would consume any asset class with higher risk weight encouraged by Basel. In so, instead of increasing diversification, it actually reduces it, and by so doing increasing risk.

Again, RWAs regulation aims at relative prices for lending and investment banks rather than directly restricting amount or asset risks. Regulators—in the absence of price discovery provided by day-to-day markets—have little hope of achieving relative price efficiency that is sufficiently dynamic and reflective of underlying risks and the dangers that risks will change.

In contrast, concentration limits on asset class exposure for the economy as a whole, or simply leverage restrictions (assets–equity of each financial firm not greater than 15:1, for instance), or an asset risk restriction (loan-to-value of mortgages not to exceed 80%, for example), are more likely to be robust and countercyclical macroprudential tools. They do not directly address systemic risk but at least offer hope of limiting risks of individual financial firms and asset classes.

Acharya (2012) argues that instead of admitting these flaws, the committee offered a new set of rules and guidelines that, in many ways, mirror the previous two attempts. While the Basel III process focuses on using more stringent capital requirements to get around some of these issues, it ignores the financial system's crucial market and regulatory failures. Haven highlighted both pros and cons of Basel III; we now move to analyse the impact it has had on crisis probability.

2.4 Methodology Literature

Bussiere and Fratzscher (2006) used a logit model to analyse crisis. They emphasised the difference between using a fixed-effects model and a random-effects model. Showing how fixed effects are equivalent to country dummies and focused on the within information only. As such, they constitute a loss of information, but the estimates are unbiased. Whereas Fragoso et al. (2018) suggested using random effects as it provides more efficient estimates because they do not consider country effects as fixed but as random and combine more efficiently the between and the within information. However, they concluded results could be potentially biased as it assumes that individual-specific effects are uncorrelated with independent variables. To help us decide what model (i.e. fixed-effects or random-effects) is a better fit for data collected in this research; the Hausman test was carried out.The Hausman test is sometimes described as a test for model misspecification. In panel data analysis (as the case here), the Hausman test can help us to choose between fixed effects model or a random effects model. The null hypothesis is that the preferred model is random effects; The alternate hypothesis is that the model is fixed effects. Essentially, the tests looks to see if there is a correlation between the unique errors and the regressors in the model. The null hypothesis is that there is no correlation between the two. We also applied marginal effects analysis to help with final interpretation of analysis (see Cameron and Trivedi, 2009).

It is important to highlight at this point that there are specific problems with the logit regression in situations when there are many potential explanatory variables. Firstly, putting all possible variables in one regression can significantly increase the standard errors when irrelevant variables are included. Secondly, the use of sequential testing to exclude irrelevant variables can lead to misleading results since there is a possibility to exclude a relevant variable every time the test is done. Equally, estimation results are often not robust to small changes in model specification, making credible interpretations of the results hazardous. Proper treatment of model uncertainty is clearly essential. One such treatment is model averaging, where the investigator aims not to find the best possible model but rather to find the best possible estimates. Each model contributes information about the parameters of interest, and all these pieces of information combine to take into account the trust we have in each model based on our prior beliefs and the data. In a sense, all estimation procedures are model averaging algorithms, although possibly extreme or limiting cases.

One of the ways to overcome these problems is the implementation of the Bayesian model averaging (BMA). This will be used for robustness check of our logit analysis here as it takes into account the uncertainty of models, considering their combinations and weighting them in accordance with their performances. This technique has been used in relation to early warning models by Cuaresma and Slacik (2009), who studied currency crises, and then Babecký et al. (2012) did a research dealing with banking, debt and currency crises. Babecký et al. (2012) also highlighted that putting all potential regressors (as done with the logit model) would likely inflate standard errors when irrelevant variables are included in the model. Using sequential testing to remove variables that are not important can cause misleading results due to excluding important variables. Overcoming these issues requires the use of BMA, which takes into account model combinations and weighting variables according to their model fit.

Echoing above, Hoeting et al. (1999) stated that the earliest use of model averaging relates to a study base on airline passengers. He showed the use of BMA for model selection could be attributed to the work of Leamer et al. (1978). It highlighted that the fundamental idea of BMA accounts for uncertainty associated with model selection. The application of BMA was also used by Fernandez et al. (2001) and Doppelhofer and Miller (2004) in growth regressions. It is showing that the Bayesian model averaging provides a formal probabilistic framework to deal with model uncertainty.

Ho (2015) also highlighted the importance of using BMA in dealing with model uncertainty. Raftery and Zheng (2003) also mentioned that BMA has important statistical properties that address not only the inflated t-statistics but also maximises the predictive performance while minimising the total error rate when compared to any individual model. BMA attraction lies in the fact that it addresses questions such as: what is the probability that a model is correct? How likely is it that a regressor has an effect on the dependent variable? BMA does this via the Posterior Inclusion Probabilities (PIP) that result from summing up posterior model probabilities across all models that included the regressor. Chow (1979) and later refined by Kass and Raftery (1995) developed a general rule that shows the effect-thresholds for posterior inclusion probabilities. They showed PIP with $<$50% are seen as evidence against an effect or weak effect of the regressor, whereas anything above 50% can be accepted to have a positive and robust effect. More recently, Taha Zaghdoudi (2016) restated that the robustness of a variable in the explanation of the dependent variable can be captured by the probability that a given variable is included in the regression. For this, the posterior inclusion probability is used. It captures the extent to which the robustness of the relationship of a potential explanatory variable to the dependent variable can be ascertained. Variables with large PIP can be considered as robust determinants of the dependent variable, while variables with low PIP are deemed not to be robustly related to the dependent variable.

Fragoso (2018) also shows that Bayesian Model Averaging (BMA) is an extension of the usual Bayesian inference methods in which one does not only models parameter uncertainty through the prior distribution but also model uncertainty obtaining posterior parameter and model posteriors using Bayes' theorem and therefore allowing for direct model selection, combined estimation and prediction.

2.5 Data

The macroeconomic movements that crystallise risks particular to banking systems, e.g. interest rate, credit, liquidity and market risk, have been the key determinants of banking crises in the last 20 years (Emre and Thomson, 2005). Going by this, then it is logical that variables for this analysis to measure the probability of a crisis occurring would encapsulate those mentioned above in some manner. In order to capture developments in the economy prior to the crisis and to avoid endogenous effects of crises on the explanatory variables, all variables are lagged by one period, apart from real house price growth, which has three lags (Barrell et al., 2009). It is probably the case that house price growth is a proxy for other driving factors, which is why it has a longer lag than the other variables. The growth rate of some of the variables were also taken where stationarity is not achieved after taking first difference (Cameron and Trivedi, 2009).

2.5.1 Dependent Variable

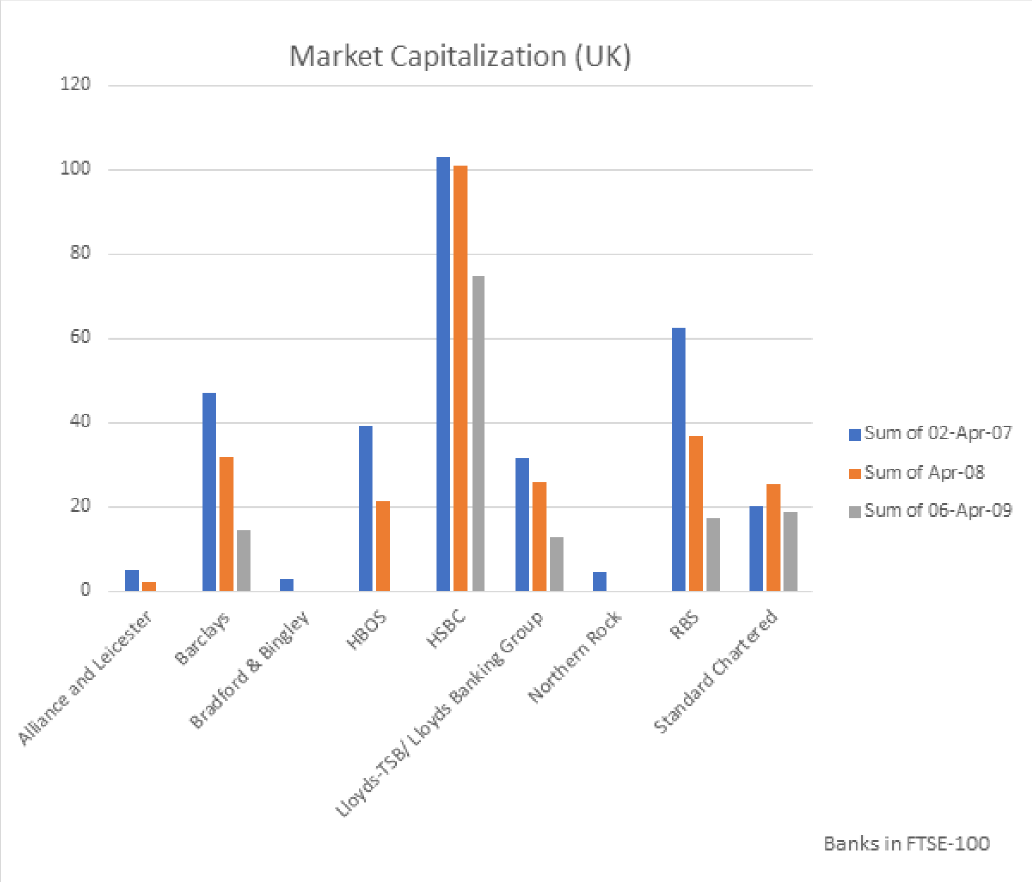
The literature has shown that even after identifying important variables that can predict the crisis, there still remain the inconsistency in the banking crisis dependent variable, which is necessarily defined with a degree of subjectivity as shown by Kaminsky and Reinhart (1999), Demirgüç-Kunt and Detragiache (1998) and Eichengreen and Arteta (2002).
There is no unique quantitative variable for a banking crisis (Bussiere and Fratzscher, 2006). The problem lies in the fact that a banking crisis is an event, so proxies for banking crises do not necessarily have a perfect correlation with banking crises themselves. For instance, if we were to use a measure for banking insolvency, such as aggregate banking capital, we would need to define a lower bound threshold for a crisis event. However, government intervention or deposit insurance could prevent a crisis while the threshold is still be violated. Another issue is that not all crises stem from the liabilities side. Kaminsky and Reinhart (1999) showed problems in asset quality could also erode banking capital so that a single proxy variable would not pick up all crisis events. As a result, a dummy is constructed based on several criteria, which vary according to the study and often using accurate, post-crisis data. Caprio and Klingebiel (1996) focused on the solvency side of a crisis and defined a systemic crisis as an event when "all or most of the banking capital is exhausted. They identified 93 countries as having experienced systemic crises between1980 - 2002.

Demirgüç-Kunt and Detragiache (1998), used a more specific set of four criteria, i.e. where achievement of at least one of the conditions was a requirement for a systemic crisis; otherwise, bank failure was non-systemic. The dependent variable takes a value of one if at least one of the four conditions are satisfied: (1) The proportion of non-performing loans to total banking system assets exceeded 10%, (2) Public bailout cost exceeded 2% of GDP, (3) Systemic crisis caused large-scale bank nationalisation, (4) Extensive bank runs were visible, or if not, emergency government intervention was visible.

This definition of the crisis dependent variable has been adopted as a mainstream definition that was adopted by the international monetary fund, World Bank, and work of Laeven and Valencia (2018) with the addition of Deposit freeze and bank holidays that captures conditions when the government placed restrictions on deposit withdrawals or a bank holiday. Therefore, it is reasonable given broad consensus to equally adopt the same here, less the 5^{th} addition by Laeven and Valencia (2018) given it occurred in Iceland, a country not part of current study.

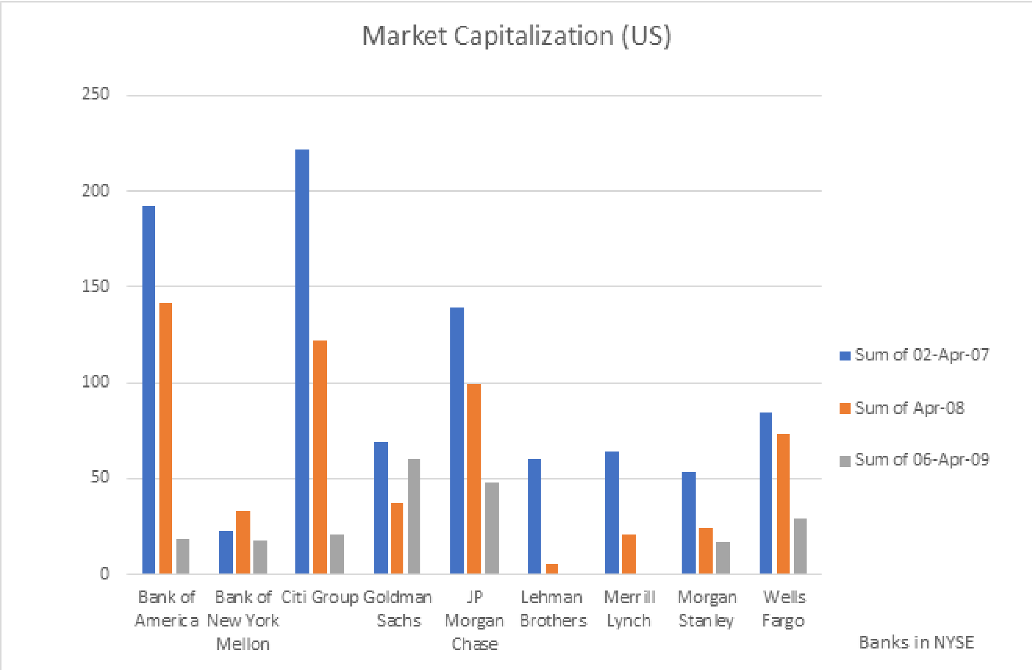
By way of depicting the progress of the crisis or the dependent variable as described above: Graphs 2.1 and 2.2 below showed how the capitalisation of major financial institutions in the UK and US were affected between 2007 – 2009. Some of them failed within the period, while others experienced a variation of the other conditions used to define the dependent variable.

Figure 2.1: Market Capitalization (UK)



Notes: Market Capitalization, capturing event surrounding dependent variable in the UK. There were about 46 financial service firms failure, and all UK banks needed some assistance, while UK government engaged in Quantitative Easing program from 2009 to 2016 that stood at £435 billion (all banks met the criteria set out by the dependent variable). Source: Author.

Figure 2.2: Market Capitalization (US)



Notes: Market Capitalization, capturing event surrounding dependent variable in the US. There were 168 banks failures in the US within this time period, despite Troubled Asset Relief program that pumped about 475 billion under Dodd-Frank Act to stabilize the economy. Outside the 168 failed banks, most financial institutions benefitted from TARP, meeting the criteria set by dependent variable). Source: Author.

It is noteworthy to mention that Demirgüç-Kunt and Detragiache (1998), admitted to relying on the judgement if there was insufficient evidence to support their crisis criteria. On that basis, they established 31 systemic crises in 65 countries over the 1980–1994 period. They further conducted a follow-up study and extended the sample to 1980–2002. Using the same criteria as before, they found 77 systemic crises over 94 countries.

2.5.2 Explanatory Variables

The explanatory variables chosen are based on previous literature and theory about the factors that caused the crisis, as already discussed earlier. Real GDP and real short-term interest rate are used to capture macroeconomic and non-performing loan shocks that affect the banks. Real interest rates also captures the banking sector liberalisation, which in turn captures the fragility of the sector because of increased opportunities for excessive risk-taking. Inflation (as associated with nominal interest rate) is used to capture macroeconomic mismanagement that fuelled the bubble due to excessive credit.

Barrell et al. (2010b) equally showed that when considering the variables that are important for measuring the cause of the crises, then the current account deficit should be included. This is because it has led to the growth of global imbalances that is deemed as part of the determinants of the crisis. Due to such pressure, global real interest rates fell after 2001Q1, and real long-term rates were probably 100 or more basis points below their level of the previous decade. This in turn contributed to rapid credit expansion and rising asset prices which preceded the crisis". A number of potential links are traced from current account deficits to the risk of banking crises. For example, deficits may accompany monetary inflows that enable banks to expand credit excessively, and they may accompany an overheating economy. This may both generate and reflect a high demand for credit, as well as boosting asset prices in an unsustainable manner.

Equally, McKinnon and Pill (1997) also showed capital inflows in a weakly regulated banking system with a safety net may lead to over-lending cycles, consumption booms, rising asset prices and further increases in current account deficits.

In terms of macroeconomic indicators, as discussed by Beck et al. (2006), variables such as the growth of real GDP, changes in terms of trade and inflation can be seen to capture macroeconomic developments that affect banks asset quality. The vulnerability of banks to sudden capital outflows may be indicated by the ratio of their deposits to foreign exchange reserves. Credit growth may indicate lax lending standards as well as potentially triggering an asset boom. A lax monetary policy, as indicated by the short-term real interest rate may also induce lax lending and feed asset bubbles. Fiscal deficits may also affect the risk of crises by overheating the economy. A large fiscal deficit also reduces the scope to recapitalise banks should difficulties emerge, making a systemic crisis more likely. Institutional variables such as a deposit insurance scheme may lead to greater moral hazard for banks. Structural features of bank regulation, legal framework and economic freedom (Barth et al. 2004) may also be used as institutional controls.

Following the discussion above, I include macroeconomic, banking-sector and policy variables from the existing literature as potential predictors. Besides the current account/GDP ratio, macroeconomic variables are real GDP growth, inflation, and real house price growth. Banking variables are the ratio M2/Foreign Exchange Reserves, real domestic credit growth, Banking sector leverage, Liquidity ratio, as captured by Basel III threshold ratio's (capital adequacy ratio, leverage ratio and liquidity ratio) have been added. Policy variables are the real interest rate and the fiscal surplus/ GDP ratio (%). The databases used for this research include the IMF sector soundness indicators, World Bank WDI, BvD BankScope, SNL Banker, Federal Reserve and Bank of England databases. It is also important at this point to mention that Basel III ratios were used alongside previous Basel ratios that were supposed to come to effect around the crisis period that started in 2007 to measure the impact of Basel thresholds on crisis, while liquidity and leverage ratios pre 2008 are collected as traditionally defined.

2.5.3 Descriptive Statistics

Table 2.2 shows the frequency of the crisis period (yearly basis) recorded from 1970 to the period of the recent crisis in 2008 in both UK and US. Where '1' signifies the occurrence of a crisis and '0' shows the absence of crisis. In total there were 17 years in the UK (1973 – '76, 1981 – '84, 1991–'93, 1995, 2000 – 2003, 2007 – 2008) that meet the crisis criteria set out above and 23 years in the US (1973 – '75, 1977 – '82, 1984–'91, 2000 – 2003, 2007 – 2008) Reinhart and Rogoff (2011). Table 2.3 describes the statistics for all independent variables covering the same period as Table 2.2. It takes into account the number of observations used for analysis after lagging the respective variable(s). The table also shows the mean, standard deviation, minimum and maximum values for these variables. Consistent with the analysis undertaken, further descriptive statistics are captured in Tables 2.4. These effectively capture the changes that have occurred in independent variables that highlights the lead up to the crisis and period that regulation was implemented.

Table 2.2: Crisis Frequency

CRISIS	FREQ.	PERCENTAGE
0	43	55
1	35	45
TOTAL	78	100

Notes: Descriptive statistic of systemic banking crisis from 1970 to 2008. The table shows 43 years without crisis, while 35 years had some kind of crisis that ranges from banking, stock-market, currency or debt crisis between UK and US.

Table 2.3: Descriptive Statistics 1970 - 2008

Variable		Mean	Std. Dev.	Min	Max	Obs.
Cap. Adeq. ratio	overall	4.058	5.392	0.000	14.000	76
	between		0.589	3.625	4.458	02
	within		5.376	-0.400	14.433	38
Liquidity ratio	overall	6.537	12.043	0.000	31.180	78
	between		9.244	0.000	13.073	02
	Within		10.087	-6.537	24.643	39
Leverage ratio	Overall	2.730	3.612	0.000	9.900	76
	Between		1.158	1.878	3.516	02
	Within		3.517	-0.786	10.752	38
Inflation	Overall	5.551	4.572	0.797	24.207	76
	Between		1.200	4.703	6.400	02
	Within		4.492	-0.051	23.359	38
Real interest rate	overall	3.149	3.594	-12.172	8.720	76
	Between		1.991	1.741	4.556	02
	Within		3.303	-10.765	7.846	38
Priv.sect.credit/GDP	overall	3.319	7.067	-19.132	31.788	76
	Between		0.809	2.746	3.891	02
	Within		7.043	-18.560	31.216	38
Real Property growth	Overall	58.408	22.375	22.874	114.409	72
	Between		21.313	43.338	73.479	02
	Within		16.441	37.945	113.223	36
Real dom. credit growth	Overall	0.054	0.251	-0.723	0.892	76
	Between		0.052	0.018	0.091	02
	Within		0.248	-0.759	0.855	38
M2/foreign exch. res	Overall	-0.111	1.301	-3.768	1.958	76
	Between		0.070	-0.161	-0.061	02
	Within		1.300	-3.719	2.008	38
Fiscal surplus/GDP	Overall	-0.145	0.891	-2.361	2.180	76
	Between		0.024	-0.162	-0.128	02
	Within		0.890	-2.344	2.197	38
Real GDP growth	Overall	-0.176	2.416	-8.972	6.543	76
	Between		0.014	-0.186	-0.167	02
	Within		2.416	-8.963	6.534	38

Notes:Descriptive statistic of explanatory variables with total observations, variations, mean, standard deviation, minimum and maximum figures from 1970 to 2008. The between variation shows variation 'between' each variable in the panel, while 'within' shows variation of a variable overtime.List of all explanatory variables with full definition, source, frequency and lagging details in appendix.

Table 2.2 shows about 45% crisis occurrence, supporting the rationale to cover the historic period, not only to provide a balanced approach to the analysis but also in line with previous literature when analysing crisis period. While there are 11 regressors, the focus here remains on those variables with statistical significance within the model and Basel III regulatory variables. Comparing the capital adequacy ratio from Table 2.3 above and that of Table 2.4 below confirms the earlier highlighted fact that financial institutions within the UK/US have taken steps to meet the new regulatory requirements. The Capital adequacy ratio had a mean of 4.058 and a maximum of 14 in Table 2.3 and 14.625 and 19.62 in Table 2.4, showing an increase in the ratio that highlights the impact of the new regulation. Bank liquidity ratio mean and maximum figures rose from 6.537 and 31.180 to 25.634 and 36.530 respectively, and Bank Leverage ratio from 2.730 and 9.9 to 7.327 and 9.580 respectively. The Leverage ratio increase reflects the change in how the leverage ratio is calculated and had the greatest impact on reducing the crisis probability. The statistics for GDP shows that over the period, the mean value of GDP growth has improved from -0.176 to -0.048, while the maximum growth has remained the same at 6.54. The mean value for Real house price growth, as expected, has increased from 55.50 to 66.199, possibly reflecting the bubble within the housing market.

Table 2.4: Descriptive Statistics 2009 - 2018

Variable		Mean	Std. Dev.	Min	Max	Obs.
Cap. Adeq. ratio	overall	14.625	2.840	9.440	19.620	22
	between		2.209	13.063	16.186	02
	within		2.347	11.002	18.058	11
Liquidity ratio	overall	25.634	10.368	0.000	36.530	22
	between		10.888	17.935	33.333	02
	Within		6.738	7.699	37.469	11
Leverage ratio	Overall	7.327	1.734	4.413	9.580	22
	Between		2.151	5.806	8.848	02
	Within		0.763	5.879	8.546	11
Inflation	Overall	2.155	1.052	-0.356	3.839	22
	Between		0.230	1.992	2.318	02
	Within		1.039	-0.193	4.002	11
Real interest rate	Overall	1.279	1.882	-1.481	5.249	22
	Between		1.723	0.060	2.498	02
	Within		1.409	-0.263	4.074	11
Priv.sect.credit/GDP	Overall	1.270	11.298	-19.132	23.099	22
	Between		0.287	1.068	1.473	02
	Within		11.296	-19.334	23.302	11
Real Property growth	Overall	78.421	9.432	86.139	117.950	22
	Between		2.962	96.326	100.515	02
	Within		9.185	84.045	115.855	11
Real dom. credit growth	Overall	-0.071	0.261	-1.000	0.336	22
	Between		0.027	-0.090	-0.052	02
	Within		0.260	-0.981	0.355	11
M2/foreign exch. res	Overall	-0.053	2.129	-4.931	3.194	22
	Between		0.187	-0.185	0.079	02
	Within		2.124	-4.844	3.326	11
Fiscal surplus/GDP	Overall	0.113	0.924	-1.875	2.046	22
	Between		0.279	-0.085	0.310	02
	Within		0.901	-1.678	1.978	11
Real GDP growth	Overall	-0.048	2.213	-3.715	5.882	22
	Between		0.018	-0.061	-0.036	02
	Within		2.213	-3.703	5.895	11

Notes:Descriptive statistic of explanatory variables with total observations, variations, mean, standard deviation, minimum and maximum figures from 2009 to 2018. The between variation shows variation 'between' each variable in the panel, while 'within' variation shows variation of a variable overtime.

2.6 Methodology

2.6.1 Logit Model

The use of EWS has been applied on many empirical literatures to explain crisis such as those applied by Berg and Patillo (1999), Demirgüç-Kunt and Detragiache (1998), Eichengreen and Arteta (2002), Furman et al. (1998), Honohan (1997), Kaminsky and Reinhart (1999) amongst others. EWS has two main approaches to dealing with crisis explanation, i.e. 1, Signal method and 2, use of econometric techniques. The former is a non-parametric method, and a variable has a threshold that, if breached, acts as a signal for an impending crisis, as used by Kaminsky and Reinhart (1999). While the latter allows the use of multivariate explanatory variables to establish the relationship between dependent crisis variable and independent variables. It employs the use of probabilities to show the relationship between discrete dependent variables (Tularam and Subramanian, 2013). We use a logit model to achieve such end here.

The logit model is a binary dependent variable model. Where its simplest form is a linear probability model (LPM). It is based on the assumption that the probability of an event y occurring is linearly related to a number of explanatory variables say; X_1, X_2, $X_3 \ldots X_k$, Hence, the linear probability model can take the form

$$y = p(y = 1) = \beta_1 + \beta_1 X_2 + \beta_1 X_3 + \cdots + \beta_1 X_k + \mu \qquad (2.1)$$

Where, y = is the dependent variable, and is made up of a series of zeroes (0's) and ones (1's) i.e. the chance of the event occurring or not. Although this can then be estimated using standard ordinary least square regression, and the fitted values in equation 1 becomes the estimated probabilities of y = 1 for each observation. The slopes are then interpreted as the change in the probability that the dependent variable will equal 1 for a one-unit change in a given explanatory variable, holding the effect of all other explanatory variables fixed (Brooks, 2019). The only problem with this is the fact that the probability value outcome can be outside the desired value of zero or one. To overcome this problem amongst others associated with LPM, we use a logit model. It applies an S shape type function to allow the probability values to remain within the desired boundaries. This function is estimated as

$$F(z) = \frac{e^{z}}{1 + e^{z}} = \frac{1}{1 + e^{-z}} \tag{2.2}$$

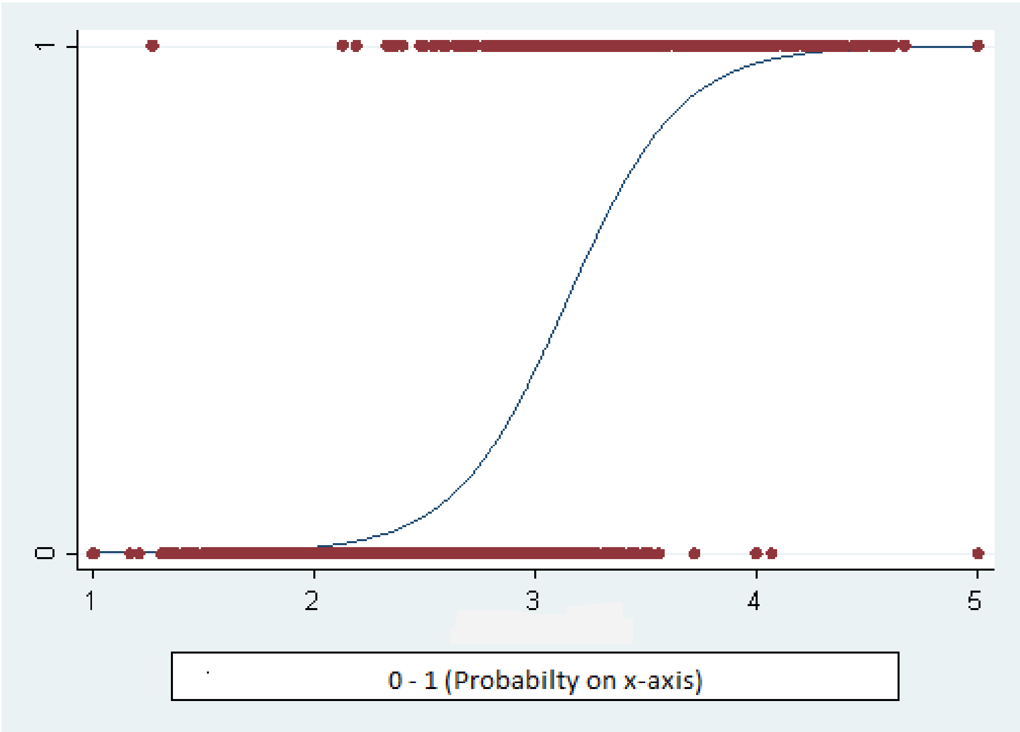
Where z is any random variable and e is an exponential within the logit model and F the cumulative logistic distribution. The logistic model is therefore estimated via

$$P = \frac{1}{1 + e^{-(\beta 1 + \beta 2x2 + \cdots + \beta kXk + \mu)}} \tag{2.3}$$

Where: P is the probability that y = 1, and 0 and are asymptotes to the function as suggested by the graph 1 below. Showing that the probabilities never reach exactly zero or one.

Equation 2.2 also show that as *z* tends to infinity, e^{-z} tends to zero and as $\frac{1}{1+e^{-z}}$ moves to 1, *z* moves to minus infinity. Therefore, to estimate the model, maximum likelihood method rather than OLS is required.

Figure 2.3: Logit graph



Notes: Logit model, showing a bounded outcome between one and zero.

Source: UCLA (2021).

The multivariate logit form used by Davis and Karim (2008) and Barrell et al. (2009) and adapted here is of the functional form;

$$\mathrm{Prob}(Y_{it}= 1) = F(\beta X_{it})=\frac{e^{\beta 1}X_{it}}{1 + e^{\beta 1}+X_{it}} \tag{2.4}$$

Accordingly, the dependent binary variable; a dummy of crises, takes a value of zero (0) when there is no crises and the value of one (1) when crises occurs and is denoted by;

Y_{it} is the independent variable for country $_i$ at time $_{t,}$ therefore
y = {1 with probability p, or 0 with probability 1- p}.

P (i, t) denote the probability dummy variable for crises occurring as one and zero otherwise in i country (US/UK) at time t (1970 – 2017).

β is the vector of coefficients hypothesizing whether a crisis occur or not

X_{it} serves as the vector of explanatory variables and

$F\beta X_{it}$ is the cumulative logistic distribution function.
The log likelihood function that is use to obtain the actual parameter estimates then becomes;

$$\mathrm{Log}_e L = \sum_{i=1} n \; . \; \sum_{t=1} T \; .[\left(Y_{it}\mathrm{Log}_e F\left(\beta' X_{it}\right)\right) + (1-Y_{it})\,\mathrm{Log}_e\left(1 - F\left(\beta' X_{it}\right)\right)] \tag{2.5}$$

The sign on the above coefficients are then interpreted directly to show: a positive or negative relative relationship with the crisis probability; however, interpreting the values are not as straightforward. Davis and Karim (2008) highlighted that the parameters obtained by maximising the function above are not constant marginal effects of X_{it} on the crisis probability. Since the variable's effect is conditional on the values of all other explanatory variables at time t, rather the coefficient β_i represents the effect of X_i when all other variables are held at their sample mean values.

Therefore, to directly compare the individual contributions of each variable to crisis, their marginal effects can be computed for their mean values as shown by Greene (2000) or at a specific year before a crisis unfolds. Furthermore, Cameron and Trivedi (2009) stated results interest for the purposes of interpretation from logit models need lie in determining the marginal effects of change in a regressor on the conditional probability that *y* =1. Given the interest here is understanding the impact of some particular explanatory variables, calculating the marginal effects is necessary (Koop, 2008). This is given by;

$$\frac{\exp(\beta X_{i})}{1+\exp(\beta X_1)} \text{ x } \frac{1}{1+\exp(\beta X_i)}\beta \tag{2.6}$$

2.6.2 Bayesian Model Average

The basic idea of BMA from above as used within EWS literature and here is that: when there are many plausible models, inference should be based not on a single model, but rather on the average of all models. This methodology avoids the a-priori selection of a subset of regressors. By making inferences based on a weighted average over the model space, the resulting estimates can better reflect the uncertainty in the estimates (Babecký et al., 2013). Given that Basel III liquidity ratios have been added to the explanatory variables, further statistical test would be appropriate to establish if they should remain within the final model. The essence of using BMA here is for robustness checks on these regressors, i.e. if the regressors of Basel III are relevant in the model via the calculation of posterior inclusion probabilities (PIP) % as explained above. Essentially, BMA provides further robustness for the analysis. This is especially important since we already know that small changes in any particular model leads to estimation results that are not robust, such that final credible interpretation becomes uncertain. BMA, therefore, provides not only the best possible model but also the best possible estimates. This is because each model contributes information about the parameters of interest, and all these pieces of information take into account the trust we have in each model base on our prior beliefs and on the data.

Given that we are interested in crisis probability denoted as y. Then the posterior distribution of y given the data collected D becomes

$$\mathrm{pr}(y \mid D) = \sum_{k=1} k\mathrm{Pr}(y \mid M_k, D)\ \ \mathrm{Pr}(M_k|D) \tag{2.7}$$

This is an average of the posterior distribution under each of the model considered, weighted by their posterior model probability. In equation (2.7), $M_{1\ldots}$ M_k are the models considered. The posterior probability for model M_k is then given by;

$$\mathrm{Pr}(M_k \mid D) \ = \ \frac{p_r[D|M_k]\ p_r[M_k]}{\sum_{l=1}^{k} p_r[D|M_l]\ p_r[M_l]} \tag{2.8}$$

where,

$$\mathrm{Pr}(M_k \mid D) \ = \int \mathrm{pr}(D|\theta k,\ Mk)\ \mathrm{pr}(\theta k|Mk)\ d\theta k \tag{2.9}$$

equation 2.9 becomes the integrated likelihood of the model $M_{k.}$

θ_k is the vector of parameters of model M_k (e.g. for regression $\theta = (\beta, \sigma^2)$)

$\mathrm{Pr}(\theta_k|M_k)$ is the prior density of θ_k under model M_k

$\mathrm{Pr}(D|\theta_k, M_k)$ is the likelihood

$\mathrm{Pr}(M_k)$ is the prior probability that M_k is the true model (given one of the models considered is the true model) and all probabilities are condition on M, i.e. the set of all models being considered (Hoeting et al., 1999).

BMA estimation, therefore, proceeds by initially estimating the parameters conditional on a selected model. Thereafter the estimator is computed as a weighted average of these conditional parameters. To achieve this averaged model: the posterior model probabilities are used as considered under the Bayes' theorem:

$$P\ (M_i\,|y,X)\,\alpha\ x\ P(y\,|\,M_i,X)\ x\ P(M_i) \tag{2.10}$$

Where $P\ (M_i\,|y,X)$ represents posterior model probability, which is proportional to the marginal likelihood of the model $P(y\,|\,M_i,X)$ multiplied by the prior probability of the model $P(M_i)$.

The robustness of a variable in the explanation of the dependent variable is then captured by the probability that a given variable is included in the regression via the calculation of Posterior Inclusion Probability (PIP).

PIP captures the extent to which we can evaluate the robustness of the relationship of a potential explanatory variable to the dependent crisis variable. Variables with large PIP can be considered as robust determinants of the dependent variable, while variables with low PIP are deemed not to be robustly related to the dependent variable. As earlier explained, for the purpose of this research, we remain focused on the impact of Basel threshold variables, hence informing why they have been added to the model as focused variables (knowing that other variables could potentially have a greater PIP outcome than these variables).

2.7 Results

To capture the impact of regulation on the crisis probably; the data is divided into 2 sample periods. Part of the rationale for this is that the crisis dependent variable extended to 2010 period. This explanation comes from the actions of Bank of England quantitative easing (QE), a large stake in major banks ownership, Federal Reserve's troubled asset relief program (TARP), in the absence of other earlier events such as bank closures/failures. Equally, Basel III became operational in 2013 and the thresholds in question fully complied with in January 2019. The adjustment period allowed banks to meet these thresholds, and the data collected showed the required thresholds are mostly met at the time Basel III was announced in December 2010 when the Basel Committee on Banking Supervision (BCBS) announced a package of reforms known as Basel III (BCBS, 2010b). As such, the first sample covers the whole period, as done by most of the previous works of literature, which is 1970, while the subsample is from 2010 to 2018. This sample allows the analysis to provide a clear impact with the regulation has had on crisis probability.

2.7.1 Model Interpretation

In total, we ran seven logit regressions. In order to capture developments in the economy prior to the crisis and to avoid the endogenous effect of crises on the explanatory variables, all variables are lag by one period. Models 'A' to 'D' are referred to as full regressions, in the sense that they cover the whole sample period (1970 – 2018), while models 'E' to 'F' covers the period from 2010 to 2018 (justification for sample already mentioned earlier). This is similar to Demirguc-Kunt et al. (2013), when examining the impact of banking regulatory variables and crisis had on stock returns. At each stage, the variable(s) that are not statistically significant are removed from the next regression. Regression A is used for the Hausman post estimation test to determine if a random or fixed effect model is more appropriate. Further, a marginal analysis test is applied to assess the impact of each explanatory variable on the probability of a crisis, similar to Barrell et al. (2010a). Finally, BMA is used for explanatory variables robustness check, complementing previous empirical application of BMA as used by Ho (2015), Christofides et al. (2016), Babecký et al. (2012), Hamdaoui (2017), and Cuaresma and Slacik (2009).

Table 2.5: Panel multivariate logit model (Models A – D)

Variable	Model A	Model B	Model C	Model D
Capital Adeq. ratio	-0.395***	-0.436***	-0.098***	-0.024**
	-0.002	-0.006	-0.006	-0.042
Liquidity ratio	-0.129***	-0.117***	-0.084***	-0.015**
	0.003	-0.003	-0.003	-0.016
Leverage ratio	0.615**	0.603**	0.252**	0.058*
	0.042	0.032	-0.033	-0.048
Inflation	0.000	0.054	–	–
	-0.627	0.312	–	–
Real interest rate	0.072*	0.112***	–	–
	0.061	-0.021	–	–
Priv.sect.credit/GDP	-0.055	–	–	–
	-0.253	–	–	–
Property price	0.064*	0.066*	0.059*	
	0.003	0.000	0.000	
Domestic credit	-1.095	–	–	–
	-0.351	–	–	–
M2/FRX reserves	-0.303	–	–	–
	-0.154	–	–	–
Fiscal surplus/GDP	0.051	–	–	–
	-0.889	–	–	–
Real GDP growth	-0.351***	-0.346***	-0.374	–
	0.007	0.003	-0.428	–
constant	-3.421	-3.101	-2.702	
	0.027**	0.001***	0.001***	
Crisis Variable: Y = 0 (no crisis), Y = 1 (crisis)				

Notes: The panel logit probability model estimated in this table is Banking Crisis probability; (Country = j, Time = t) = a - b1 capital adequacy ratio j, t - b2 bank liquidity ratio j, t + b3 bank leverage ratio j, t + b4 inflation j, t + b5 real interest rate j, t + b6 credit as a % of GDP j, t + b7 real house price growth j, t + b8 broad money as a % of foreign reserve growth j, t + b9 government deficit/surplus as a % of GDP + b10 government current account as a % of GDP + b11 real GDP growth + e j, t. The dependent variable is a crisis variables with two outcomes: Yj,t = 1 for year of crisis and Yj,t = 0 years not categorized as crisis period.

Looking at Table 2.5, the logit model's log-likelihood ratio iteration shows that the model converged and the model is different from zero. The model's statistical significance is also established as our Prob > chi2 = 0.0243 is less than 5%. Meaning that our model is able to provide explanation with respect to crisis probability using the explanatory variables within the model.

Although some of the variables in model 'A' have not proved statistically significant, the observed relationship of all variables from earlier theoretical assumptions to crisis probability are all as expected. Model A shows an inverse relationship between real economic growth and the probability of a crisis occurring and a positive relationship between growth in house prices and crisis probability. This follows the theoretical assumption on the relationship between the existence of bubbles and these variables. Equally, the leverage ratio has a positive relationship to crisis probability, as it indicates more risk. However, a point to note here is bank leverage, as traditionally defined, is different from Basel III bank leverage (tier 1 capital dividing unweighted total average asset). Hence Basel leverage ratio behaves inversely to crisis probability, as shown further in the analysis, while traditional bank leverage (debt to equity ratio) has a positive relationship, and given we have much more data points (1970 – 2009) from this sample that is not Basel leverage defined (2010 – 2018), the relationship is positive.

The Model also shows that at a 10% level of significance, the interest rate remains a significant variable in explaining the crisis. This is similar to Demirguc-Kunt and Detragiache (2005) 's work, where they found that crisis occurred in periods of low GDP growth and high interest rates. Model B shows that real house price growth, GDP and Basel III ratios remain significant explanatory variables for the crisis, while real interest rate ceases to be a significant predictor for the crisis. An explanation for this is that interest rate as a joint predictor alongside other variables is significant but not independently. This is similarly reported in the work of Davis and Karim (2008). Model C shows that real house price growth continues to provide an explanation for the crisis. It is probably the case that house price growth is a proxy for other driving factors. It is likely serving as an indicator of potential bad lending and hence of the wave of consequent defaults that frequently develop as a consequence of a house price bubble. Model D shows the importance of the new Basel III variables to crisis probability. They have remained significant throughout, showing that regulation has taken an important step towards reducing crisis probability.

The Hausman test, that test whether the unique errors (u) are correlated with the regressors was undertaken. The result suggest otherwise, i.e. differences across the panel have some influence on our crisis dependent variable as expected. Further supporting the use of random effects model instead of fixed effect.

Giving the interest in Basel thresholds, the Bayesian Model Average test is undertaken using the data set from regression A. This is appropriate, as it further confirms variables in model D remain robust in explaining the crisis. The real house price growth and real GDP growth were used as certainty variables within the model. At the same time, all the remaining were subject to a traditional 50% PIP acceptance level. Interesting all new regulatory variables have above 50% PIP. This is further confirming the importance of these variables as useful regulatory measures in dealing with the crisis.

Table 2.6: BMA model (1970 - 2018)

CRISIS	Coef.	t	pip	pip-rank
Real GDP growth	-0.063	-3.264	1	
Property price	0.009	2.620	1	
M2/FRX reserves	-0.025	-0.260	0.141	5
Capital Adeq. ratio	-0.039	-1.642	0.876	1
Liquidity ratio	-0.011	-1.171	0.69	2
Leverage ratio	0.028	0.600	0.511	3
Inflation	0.002	0.174	0.123	6
Real interest rate	0.002	0.241	0.490	5
Priv.sect.credit/GDP	-0.001	-0.250	0.141	5
Domestic credit	-0.027	-0.731	0.511	4
Fiscal surplus/GDP	0.002	0.152	0.110	7

Notes: The Bayesian model average with real house prices and real GDP growth chosen apriori due to statistical significance in model A and consensus from theory. The table shows the ranking in order of statistical significance for each variable within the model.

Generally, the BMA results show that the estimates from Basel III thresholds are robust, i.e. all three variables have a PIP above 50%. It also shows that fiscal surplus to GDP ratio to be an important variable within the model that was not picked up by the logit model even though the theory has earlier justified why it was initially included. The interest rate is also just below the 50% mark, further supporting the theory on why it was included and the logit model's result. The margins analysis that allows us directly infer from coefficients (table 2.8 below) on regression D showed the Bank liquidity ratio to reduce the crisis ratio by 1.5% over the period, while the Bank leverage ratio increased the crisis probability by 5.7%. The capital adequacy ratio minimises the probability of crisis by about 2.4%.

Table 2.7: Average marginal effects (1970 - 2018)

Variable	Coefficient
Capital adeq. ratio	-0.024**
	0.042
Liquidity ratio	-0.015**
	0.016
Leverage ratio	0.057**
	0.024

Notes: The coefficients from this table are interpreted just like normal regression, with an important caveat of the β's above show probability impact on crisis dependent variable

Logit Models E, F and G in Table 2.9 are for the sample period from 2009 to 2018. All variables that were significant in the full sample have remained as such in the shorter period sample. Comparing Basel coefficients between models D and G shows a clear improvement in the regulatory variables probabilities to reduce crisis. Where the regression from the full sample shows a modest relationship of 2.4%, 1.5%, and 5.7% for capital adequacy ratio, bank liquidity ratio, and bank leverage ratio to crisis dependent variable, respectively, the shorter sample for the same variables shows 7.01%, 5.2% and 9.7% respectively—highlighting the importance of sampling the data to capture the recent regulatory effects more accurately. The results also show an improvement over those of related literature such as Barrell et al. (2010a).

Table 2.8: Panel multivariate logit model (Models E - G)

Variable	Model E	Model F	Model G
Capital Adeq. ratio	-0.395**	-0.436***	-0.702**
	0.025	0.006	0.019
Liquidity ratio	-0.129***	-0.117**	-0.052***
	0.003	-0.003	-0.008
Leverage ratio	0.615**	0.603**	-0.969**
	0.042	0.032	-0.047
Inflation	0.000	0.055	–
	-0.627	–	–
Real interest rate	0.072	0.112	–
	0.061*	-0.102	–
Priv.sect.credit/GDP	-0.055	–	–
	-0.253	–	–
Property price	0.064***	0.066***	–
	0.003	0.000	–
Domestic credit	-1.095	–	–
	-0.351	–	–
M2/FRX reserves	-0.303	–	–
	-0.154	–	–
Fiscal surplus/GDP	0.05	–	–
	-0.889	–	–
Real GDP growth	-0.351***	-0.346***	–
	0.007	0.003	–
constant	-3.419**	-3.101***	–
	0.027	0.001	–
Crisis Variable: Y = 0 (no crisis), Y = 1 (crisis)			

Notes: Panel multivariate logit model (2009 - 2018).The panel logit probability model estimated in this table is Banking Crisis probability; (Country = j, Time = t) = a - b1 capital adequacy ratio j, t - b2 bank liquidity ratio j, t + b3 bank leverage ratio j, t + b4 inflation j, t + b5 real interest rate j, t + b6 credit as a % of GDP j, t + b7 real house price growth j, t + b8 broad money as a % of foreign reserve growth j, t + b9 government deficit/surplus as a % of GDP + b10 government current account as a % of GDP + b11 real GDP growth + e j, t. The dependent variable is a crisis variables with two outcomes: Yj,t = 1 for year of crisis and Yj,t = 0 years not categorized as crisis period.

The robustness check of variables in Table 2.10, follows the same pattern as table 2.8. The results are not significant different, with the exception of Bank leverage ratio posterior inclusion probability that is slightly below 50% level.

Table 2.9: BMA (2009 - 2018)

Variable	Coef.	t	pip	pip-rank
Real GDP growth	-0.059	-3.030	1	
Property price	-0.192	-0.961	1	
Capital Adeq. ratio	-0.033	-1.280	0.783	1
Liquidity ratio	-0.009	-1.011	0.630	3
Leverage ratio	-0.023	-0.520	0.479	5
M2/FRX reserves	0.007	1.470	0.787	2
Inflation	0.001	0.17	0.130	7
Real interest rate	0.003	0.324	0.181	6
Priv.sect.credit/GDP	-0.001	-0.222	0.133	7
Domestic credit	-0.035	-0.841	0.510	4
Fiscal surplus/GDP	0.004	0.171	0.111	8

Notes: The Bayesian model average with real house prices and real GDP growth chosen apriori due to statistiscal significance in table A and consensus from theory. PIP = posterior inclusion probability.

We have this far built on the main objective i.e. to establish the impact of recent Basel III capital requirement, bank liquidity ratio and leverage ratio have had so far with respect to reducing the probability of crisis so far.

Table 2.10: Average marginal effects (2009 - 2018)

Variable	Coefficient
Capital adeq. ratio	-0.082**
	0.017
Liquidity ratio	-0.060**
	0.036
Leverage ratio	-0.113***
	0.007

Notes: The coefficients reflect the inverse impact Basel III thresholds have had on the probability of crisis so far.

The final regression G shows these variables are statistically significant when determining the probability of crisis. de-Ramon et al. (2012) also came to same conclusion with emphasis on real house price growth, leverage and liquidity ratios. It has captured the relationship between the changed definition of Basel leverage ratio and crisis probability. This is an improvement over previous EWS literatures that have looked at liquidity thresholds and crisis probability.

The final logit regression with respect to these variables is specified as:

$$\text{Log}\left[\frac{\text{P(crisis)}}{1-\text{P(crisis)}}\right] = -0.082\text{CAR} - 0.060\text{BLIQR} - 0.113\text{BLEVR} \tag{2.11}$$

The sensitivity/marginal analysis from table 2.11 allows us to make an inference on the impact these variables currently have on the probability of a crisis. In other words, the impact regulation is having on reducing the crisis probability via these channels. These are; 8.12% for capital requirement ratio, 0.6% for bank liquidity and 11.3% for bank leverage. It can be inferred that the use of unweighted average total assets denominator when calculating the leverage has been especially useful in reducing the crisis probability due to the fact it captures both on and off-balance sheet items, given that significant risk has been moved off the balance sheet in the period building up to the crisis. This measure has allowed regulation to capture a significant amount of risk that is reflected in the probability of crisis reduction. These ratios, as compared to the general model, have shown significant improvement in reducing crisis probability. It is further supporting the regulation set out in Basel III. Regulation of these thresholds via changing what each of these ratios captures to better reflect the nature of risk and evolution of the banking balance sheet has proved to have an impact on reducing the chances of further crisis happen through these channels. However, this does not suggest that these channels are immune to be future sources of crisis in the presence of interaction with other variables that regulation, empirical evidence or analysis has not identified.

2.8 Conclusion

This chapter examined whether the recent regulatory steps that were taken after the crisis; in particular, Basel III has had an impact on crisis probability. To achieve this: the most recent data has employed that span from 1970 – 2018. The methodology used (Logit model) is similar to that used by Barrell et al. (2009) and Davis and Karim (2008). However, we contributed by using actual Basel III data as opposed to assumed increases to Basel III threshold in previous literature (i.e. these analysis were done prior to announcement and implementation of the new regulation). Another contribution is that Basel III thresholds were not established as variables for EWS model in previous analysis, this work has shown due to change in regulation, these should now be considered as part of the EWS variables. BMA was used to further justify including the new Basel III regulatory variables within the model. The analysis has shown that regulators have taken into consideration the impact that non-balance items can have on the banking sector as reflected in the new Basel III 'leverage ratio' definition. The analysis has distinctively shown the impact of this by dividing our sample period to capture the impact our new leverage ratio has on reducing crisis probability.

Our results show an inverse relationship between real economic growth and the probability of a crisis occurring and a positive relationship between growth in house prices and crisis probability. Basel leverage ratio behaves inversely to crisis probability as shown further in the analysis, while traditional bank leverage (debt to equity ratio) has a positive relationship. The analysis shows that at a 10% level of significance, the interest rate is significant in explaining the crisis. This is similar to the work of Demirguc-Kunt and Detragiache (2005), where they found that crises occurred in periods of low GDP growth and high interest rates.

Comparing Basel coefficients between the two sample period regressions shows a clear improvement in the regulatory variables probabilities to reduce crisis. Where the regression from the full sample shows a modest relationship of 2.4%, 1.5%, and 5.7% for capital adequacy ratio, bank liquidity ratio, and bank leverage ratio to crisis dependent variable, respectively, the shorter sample for the same variables shows 7.01%, 5.2% and 9.7% respectively—highlighting the importance of sampling the data to capture the recent regulatory effects more accurately. The results also show an improvement over those of related literature such as Barrell et al. (2010a). The BMA results show that the estimates from Basel III thresholds are robust.

The chapter also established the rationale for regulation and showed that, like most previous major regulations, regulation after the 2007 crisis aligns with public interest theory. The argument against deregulation was clearly outlined, the rationale behind it discussed. It has been shown that regulation or deregulation is not necessary the answer but the right kind of regulation that neither hampers growth or innovation.

The analysis has shown that, while regulation has proved to affect crisis probability, it acknowledges limitation in providing the cost of regulation. As Barrell et al. (2009) stated that regulation can be seen as a tax to the banking system, with cost not only limited to the banks but can spill over to the economy at large via cost of borrowing to household and business that can lead to a reduction in output. This onerous task is beyond the scope of this chapter and can be especially difficult to undertake currently as issues such as trade wars between the USA and China, and 'Brexit' would make it especially challenging in determining this cost. Overall, the models and analysis confirmed earlier assumptions made and the importance of Basel thresholds along with other explanatory variables.

2.9 Appendix

Table 2.11: Appendix

Variables	Description	Sources
Capital Adequacy ratio	Basel III new regulatory threshold comprising of counter cyclical buffer, capital conservation buffer, common equity, tier 1 and tier 2 capital that total 10.5 percent of total assest	Financial Soundness Indicators Database (fsi.imf.org), International Monetary Fund (IMF). http://sdmxws.imf.org.
Bank liquidity ratio	Basel III new regulatory threshold comprising of liquidity coverage ratio (LCR) and net stable funding ratio (NSFR) that requires 100 percent attainment, while traditional liquidity ratio is defined as liquid asset over total asset.	Financial Soundness Indicators Database (fsi.imf.org), International Monetary Fund (IMF). http://sdmxws.imf.org.
Bank leverage ratio	Basel III new regulatory threshold defined as tier 1 capital dividing average total asset (unweighted). Traditional leverage is debt over equity.	Financial Soundness Indicators Database (fsi.imf.org), International Monetary Fund (IMF). http://sdmxws.imf.org.
Inflation	Inflation as measured by the consumer price index reflects the annual % change in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals, such as yearly. Yearly data - Lagged 1 period.	World Bank national accounts data, and OECD National Accounts data files. NY.GDP.DEFL.KD.ZG

Real Interest rates	Real interest rate is the lending interest rate adjusted for inflation as measured by the GDP deflator. Yearly data - Lagged 1 period.	International Monetary Fund, International Financial Statistics and data files.FR.INR.RINR
Domestic credit to private sector as a % of GDP	- refers to financial resources provided to the private sector by financial corporations, such as through loans, purchases of nonequity securities, and trade credits and other accounts receivable, that establish a claim for repayment. The financial corporations include monetary authorities and deposit money banks, as well as other financial corporations where data are available (including corporations that do not accept transferable deposits but do incur such liabilities as time and savings deposits). Examples of other financial corporations are finance and leasing companies, money lenders, insurance corporations, pension funds, and foreign exchange companies. - Yearly data - Lagged 1 period.	International Monetary Fund, International Financial Statistics and data files, and World Bank and OECD GDP estimates. FS.AST.PRVT.GD.ZS.

Real house price growth	The indices of residential property prices over time. Included are rent prices, real and nominal house prices, and ratios of price to rent and price to income; the main elements of housing costs. In most cases, the nominal house price covers the sale of newly-built and existing dwellings, following the recommendations from RPPI (Residential Property Prices Indices) manual. The real house price is given by the ratio of nominal price to the consumers' expenditure deflator seasonally adjusted, from the OECD national accounts database. The price to income ratio is the nominal house price divided by the nominal disposable income per head and can be considered as a measure of affordability. The price to rent ratio is the nominal house price divided by the rent price and can be considered as a measure of the profitability of house ownership. This indicator is an index with base year 2010. Yearly data - Lagged 3 period	OECD (2018), Housing (indicator). doi: 10.1787/63008438-en (Accessed on 23 July 2018).
Broad money to total reserve ratio	This is the sum of currency outside banks; demand deposits other than those of the central government; the time, savings, and foreign currency deposits of resident sectors other than the central government; bank and traveler's checks; and other securities such as certificates of deposit and commercial paper. Yearly data - Lagged 3 period	International Monetary Fund, International Financial Statistics and data files. FM.LBL.BMNY.IR.ZS

Government balances as a % of GDP	General government deficit is defined as the fiscal position of government after accounting for capital expenditures. Comprising of ”Net lending” where government is providing financial resources to other sectors, while ”net borrowing” means that government requires financial resources from other sectors. General government net lending is calculated as: gross savings plus net capital transfers (receivable minus payable) minus gross capital formation, followed by the subtraction of acquisitions minus disposals of non-produced, non-financial assets. This indicator is measured as a % of GDP. Yearly data - Lagged 3 period.	OECD (2018), General government deficit (indicator). doi: 10.1787/77079edb-en (Accessed on 23 July 2018).
Current account balance as a % of GDP	The current account balance of payments is a record of a country's international transactions with the rest of the world. The current account includes all the transactions (other than those in financial items) that involve economic values and occur between resident and non-resident entities. Also covered are offsets to current economic values provided or acquired without a quid pro quo. This indicator is measured in million USD and % of GDP. Yearly data - Lagged 1 period.	International Monetary Fund, Global Financial Stability Report. OECD (2018), Current account balance (indicator). doi: 10.1787/b2f74f3a-en (Accessed on 24 July 2018)
Real GDP growth	Annual % growth rate of GDP at market prices based on constant local currency. Aggregates are based on constant 2010 U.S. dollars. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Yearly data - Lagged 1 period.	World Bank national accounts data, and OECD National Accounts data files.NY.GDP.MKTP.KD.ZG

Chapter 3

The Impact of Regulation on systemic risk

3.1 Abstract

The financial crisis, its cost to taxpayer and the real economy has brought about an extensive regulatory change affecting the entire financial system. Using quarterly delta conditional value at risk (ΔCoVaR; a proxy for systemic risk) from 2000-Q1 – 2019-Q4, alongside bank-level panel-data, we analyse the impact of regulation after the financial crisis of 2007 on systemic risk in the UK financial system. We estimated CoVaR using quantile regression and the Garch model before applying Kupiec (1995), Christoffersen and Pelletier (2004), and Lopez (1999) tests to establish the accuracy of our results. Our result shows that variables that capture Basel III regulation have a significant impact in reducing systemic risk. In contrast, UK specific regulation shows little to no impact in reducing systemic risk.

3.2 Introduction

The recent financial crisis has brought about a sweeping set of financial regulations that the financial industry has not had for a long time. We argue that part of the reason for these regulations is due to the cost of the crisis on the real economy. However, such a regulatory framework is hard to design and implement in practice. Indeed, historical evidence suggests that the response from authorities to financial crises may engender pervasive behaviours and encourage excessive individual risk-taking (Barth et al., 2013). It is therefore not enough that regulation or cost-benefit measurements are in place, but the analysis of the impact regulation is having on systemic risk is required to understand and further policy development. This chapter is a contribution toward such direction.

Our main contribution to the literature is analysing the impact of regulation using our systemic risk measure (ΔCoVaR) on bank-level targeted variables. We do this by establishing when regulations were announced, the compliance window from regulatory authorities, and bank-level data to show when changes fully took place. These allowed us to divide our sample into the pre-regulatory period (2000 – 2013) and post-regulation period (2014– 2019) to establish this impact. This is different from the analysis of Brunnermeier et al. (2012). Although they used conditional value at risk (CoVaR) as applied in this analysis and systemic expected shortfall (SES), their study measured the systemic risk for all commercial banks in the US for the period 1986 to 2008. Saunders et al. (2016b) also looked at the concept of “ring-fencing” in the United States with a sample divided into pre and post-crisis period. What we have done differently here is using data that reflects more accurately the time regulation came into effect (as opposed to pre and post-crisis without considering regulation, therefore capturing the impact of regulation). Whereas they used only ordinary least squares for their analysis, we started by establishing delta conditional value at risk (ΔCoVaR); a proxy for identifying the systemic risk level in our analysis. Unlike most research in this area that looked at the US or Europe, our sample used UK Banks. Other variables within our study that were differently analysed in the literature include the works of; Puzanova and Düllmann (2013); Elayan et al. (2018); Brunnermeier et al. (2012); Allen et al. (2018); Saunders et al. (2016b); Laeven et al. (2016). However, just like with the work of Saunders et al. (2016b), all these analysis use data prior to the regulatory compliance period, therefore failing to capture the impact of regulation. Meaning, our analysis considers the regulatory change in the UK and Basel III. It analyses how these regulatory variables affect systemic risk before and after they are put in place.

Our second contribution relates to the analysis of systemic risk. Previous literature (e.g. Girardi and Ergün, 2013, Huang et al., 2012a, Tobias and Brunnermeier, 2016) have used both models (i.e. CoVaR and Garch) applied here when estimating systemic risk. However, we have added accuracy tests to show the model that is more accurate when assessing systemic risk (on bank regulatory variables). This analysis provides a quantile regression (henceforth; QR) and bivariate GARCH model estimation and use an accuracy test to establish the more appropriate model for estimating 'CoVaR' that enhances the accuracy of our empirical findings.

This analysis also covers a critical gap in the literature. In comparison, some (e.g. Benoit et al., 2013, Brunnermeier et al., 2012, Engle et al., 2014, Huang et al., 2012a, Laeven et al., 2016, Saunders et al., 2014, Saunders et al., 2016b) have looked at some variables used here within the context of a financial crisis. This study considers variables that were either newly introduced (such as ring-fencing) or those that are calculated differently (e.g. leverage ratio, regulatory capital) because of changes in the regulation. Therefore, providing a clear understanding of the impact, these policies have created on systemic risk. To our knowledge, no study has specifically analysed the new set of regulatory variables in relation to their impact on systemic risk. Equally, we do not know of any research that had differentiated between the period before these regulations were in place and afterwards to established their impact or shows the behaviour they exhibit to systemic risk between the two different periods. Therefore, making a significant contribution to the literature.

The fact that financial markets move more closely together during times of crisis is well documented. Giglio et al. (2016) highlighted the crisis of 2007 occurred after a build-up of systemic risk. This led to a focus to understand systemic risk and ways governments can effectively regulate their economies to reduce it. To properly mitigate systemic risk or regulate the economy to stop its build-up, a generally agreed definition of this concept is essential. However, Guerra et al. (2016) stated that there is no unique definition of systemic risk. They highlighted this issue by acknowledging systemic risk, unlike other risks, is recognized for its effects rather than causes. It also occurs from different features due to the interconnection of many factors, making a single agreed definition currently inconclusive.

Additionally, Taylor (2010) reiterated that there is no conclusive definition of system risk; nonetheless, any definition must consider: the risk of a significant triggering event such as shocks from central bank policy, shock from external events like natural disasters or shock from the failure of a large private financial firm. It must also consider the risk of propagation (contagion) due to direct or indirect linkages between firms, and finally, any definition should include the macro-economic risk that accompanies the disruption caused. Furthermore, López-Espinosa et al. (2012); Reserve (2001); Richardson (2014); Drehmann and Tarashev (2013); Mishkin (1995); Giglio et al. (2016); Krainer (2012); Vickers (2011) and Constâncio (2015) amongst others, all defined systemic risk with different caveats.

For the purpose of this analysis, we adopt the definition provided by Kaufman and Scott (2003). They defined systemic risk as the risk or probability of breakdowns in the entire system as opposed to individual parts that are evidence by the correlation (co-movement) amongst all other parts. They also stated; it can refer to macro shocks that produce near-simultaneous large adverse effects for most or all the economy domestically or at least a sector. The understanding here is that systemic risk is the initial stage or the build-up of a toxic situation in the financial industry that, if not dealt with properly, can trigger a crisis. Consequently, our systemic risk measure captures the potential for the spreading of financial distress across institutions by gauging this increase in tail co-movement.

The most common measure of risk used by financial institutions is the value at risk (Varotto and Zhao, 2018). It focuses on the risk of an individual institution in isolation. However, a single institution's risk measure does not necessarily reflect its connection to overall systemic risk. What is, therefore, suitable for our analysis is a measure that considers not only an institution's individual risk but also risk associated with tail co-movement for the entire system. To achieve this, we apply the novel procedure put forward by Adrian and Brunnermeier (2011), the CoVaR methodology. We then apply panel regression to analyse its relationship to regulatory variables at the bank level in the UK.

As put by Richardson (2014) about economic regulation, 'regulate where there is a market failure'. The 2007 crisis is the ultimate justification for the changes witnessed in the regulatory environment of banks, hence establishing the justification for this analysis. It is not only essential to understand what are the factors that bring about systemic risk (as is the focus of the literature in this area) but to measure systemic risk before and after the crisis to establish how much impact regulation is having on systemic risk.

In essence, this chapter uses the 'CoVaR' method in determining systemic risk in the UK from 2000 to 2019 using quarterly data. We identified six major variables that regulation addressed after the crisis and used panel data regression to establish the impact these variables have on systemic risk. We estimated CoVaR using the QR and Garch model. We then applied accuracy tests to decide the best model for the analysis. We sample our data to capture the pre-regulation period and post-regulation period and analysed the impact of our variables on the systemic risk. Where previous studies have examined these variables against systemic risk proxies, we contributed by diving our sample to effectively capture the impact regulation is having on systemic risk. Our methodology also established QR as a more effective model when analysing systemic risk.

The remainder of this chapter is structured as follows; Section 2 is the literature review. Section 3 describes the data used and sources. Section 4 describes our methodology. Section 5 is the presentation of empirical findings, and section 6 is the conclusion.

3.3 Literature Review

Previous studies have established various channels that give us an understanding of why and how systemic risk evolves. For example, Adrian and Brunnermeier (2011) showed externalities that lead to spillover effects occur when an institution accepts fire-sale prices. Within the context of an incomplete market situation, this brings about an outcome that is not a 'Pareto efficient' constraint. This was empirically shown in a banking context by Bhattacharya et al. (1998). This spillover effect was also shown in a general equilibrium market setting by Stiglitz (1982) and Geanakoplos and Polemarchakis (1986). Furthermore, funding liquidity of institutions can also be subject to runs that lead to externalities (Adrian and Boyarchenko, 2012). Equally, systemic risk can be the result of risks in big firms or a herd of small firms' spillover effects. It can also result from a build-up during low volatility. We can deduct from these that; systemic risk has both cross-sectional and time-series dimension that supports the application of CoVaR developed by Adrian and Brunnermeier (2011) that is used for this analysis.

Bisias et al. (2012) conclude that the starting point for all the recent regulation is the accurate and timely measurement of systemic risk. Puzanova and Düllmann (2013) argued that the recent crisis has brought about a paradigm shift in banking regulation that moved away from a micro to a macro approach, reflecting the effects of negative externality from banks that contributes to systemic risk. They stated that the focus of macroprudential regulation should be solid capital base throughout the financial cycle and de-correlation of banks' asset values.

Allen et al. (2018) implemented an event-study analysis to determine the market's reaction to the elimination of "too big to fail" (TBTF). He concluded the market reacted negatively to the passage of Dodd-Frank and to the elimination of TBTF announced within the regulation. Brunnermeier et al. (2012) and Saunders et al. (2016b) agree that all regulatory proposals in the US, UK and the EU have the concept of "ring-fencing". They showed that banks with higher non-interest income have a higher contribution to systemic risk. They also concluded that banks with higher leverage and nonperforming loans increase systemic risk, whereas those with more liquidity and interest income lower systemic risk. Laeven et al. (2016) estimated that systemic risk grows with bank size and is inversely related to bank capital.

Given the nature of systemic risk (as earlier highlighted), it tends to be measured differently, depending on what aspect of it is being captured. Drehmann and Tarashev (2013) propose the use of the generalised contribution approach (GCA) when measuring systemic risk. They empirically applied this method to 20 major US banks to assess whether interconnectedness drives systemic importance and how it affects different participants in the interbank market. They state that systemic importance rises in the presence of an interbank market, with the rise being greater for banks with greater interbank market activity. Billio et al. (2012) propose a systemic risk measure that relies on Granger causality among firms. Their results suggest that hedge funds can provide early indications of market dislocation, suggesting systemic risk arises from a complex and dynamic network of relationships among hedge funds, banks, insurance companies, and brokers. In contrast, Giglio et al. (2016) use a nonparametric approach to derive bounds of systemic risk from CDS prices.

Huang et al. (2012a) measured the systemic risk of a banking sector as a hypothetical distress insurance premium. They defined their systemic risk measure as the insurance cost to protect against distressing losses in a banking system. They used this method on a portfolio of twenty-two major banks in Asia and the Pacific from 2005 to 2009 to illustrate the dynamics of systemic risk effects of the financial crisis to the region. They concluded that; the evolution of market perception on the systemic risk of Asia-Pacific banks was mainly driven by the risk premium component and that the marginal contribution of each bank (or bank group) to the systemic risk suggests that size is important in determining the systemic importance of individual banks. Furthermore, Huang et al. (2012b) applied the same methodology using 19 Banks covered by the US stress test to show that the elevated systemic risk in the banking sector is driven initially by the rising default risk premium and later by the heightened liquidity risk premium. They also show that the marginal contributions of individual banks to the systemic risk indicator are determined mainly through bank size that is consistent with the “too-big-to-fail” doctrine.

Acharya et al. (2017) focus on high-frequency marginal expected shortfall (MES) as a systemic risk measure. MES addresses the question of which institutions are most exposed to a financial crisis as opposed to the component of systemic risk associated with a particular institution. Each financial institution's contribution to systemic risk is measured as its systemic expected shortfall (SES). Meaning they do not address the stylized fact that risk builds up in the background during boom phases characterized by low volatility and materializes only in crisis times. They demonstrate empirically the ability of SES components to predict emerging systemic risk during the financial crisis of 2007–2009. Elayan et al. (2018) and Acharya et al. (2012) develop a closely related SRISK measure (Marginal Expected Shortfall) which calculates capital shortfall of individual institutions conditional on market stress. They both agree that non-interest income is positively correlated with total systemic risk for a large sample of U.S. banks.

Using methodologies of Marginal Expected Shortfall (MES), ΔCoVaR, SRISK, and individual-bank systemic risk premia, Weiß et al. (2014) found no empirical evidence supporting the analysis that: bank size, leverage, non-interest income or the quality of the bank's credit portfolio are persistent determinants of systemic risk across financial crises. In contrast, their results show that characteristics of the regulatory regime drive systemic risk. Using a sample of EU and American banks from 1991 to 2004, they showed European banks contribute more to global systemic risk when compared to American banks due to lower quality of loan portfolios and higher interconnectedness with the global financial system. They also found higher capital regulation reduces banks' exposure to systemic risk. Benoit et al. (2013) also used MES, ∆CoVaR and SRISK to capture SIFIs of US financial institutions. They concluded that these measures capture different aspects of Systemically Important Financial Institutions (SIFIs) and a one-factor linear regression is able to explain 83% to 100% of the variability of the systemic risk estimates, which they understand to indicate that standard systemic risk measures fall short in capturing the multiple facets of systemic risk.

Laeven et al. (2016) using ∆CoVaR and SRISK find strong evidence that systemic risk increases with bank size. Their results suggest a one standard deviation increase in total assets increases the bank's contribution to systemic risk by about one-third its standard deviation when measured by ∆CoVaR, and by about half its standard deviation when measured by SRISK. They also find evidence that systemic risk is lower in better-capitalized banks, with the effects particularly pronounced for large banks. Using data of 281 Banks from 16 European countries for the period of 2012 to 2006, Derbali and Hallara (2016) reports that high correlation between Banks returns and market returns increases to the region's systemic risk. While these measures do capture different aspects of systemic risk, ∆CoVaR addresses the stylized fact that risk builds up in the background during boom phases characterized by low volatility and materializes only in crisis times that is very important for policy monitoring, making it an appropriate measure for this study.

3.4 Data

This section provides the details of our sample construction; the variables used to calculate VaR, the 'state variables' that allows the calculation of time-variation in a joint distribution of returns (CoVaR) and the choice of independent variables included in the analysis.

Given our focus on the regulatory impact and CoVaR methodology's application, our analysis focuses on publicly traded banks in the UK. The data used covers a period starting from 2000 (Q1) to 2019 (Q4). By definition, our financial system is the total number of banks in the UK generated from Thomson Reuters DataStream and S&P Global Market Intelligence databases. This includes all 'dead firm' list, along with acquired and defunct banks. To construct the sample, we started from all publicly traded financial institutions whose headquarters is in the UK and list primary business as banking. We then screened out all securities and Investment banks, along with insurance and special finance trusts. Applying these criteria left us a total number of 16 banks from the initial population of 191 financial service institutions. For the purpose of this analysis, these criteria are essential, as the focus of regulation is mainly on banks.

3.4.1 Systemic Risk Measure and State Variables

Our systemic risk measure is ΔCoVaR. It forms the first part of our methodology and empirical analysis that relies on the VaR_q^i of individual banks. To calculate VaR, we use growth rates of market-valued total financial assets as our benchmark (X^i). This is similar to previous literature such as Laeven et al. (2016) and Tobias and Brunnermeier (2016) . More formally, X^i is calculated as

$$\mathrm{Xi} = \frac{(\mathrm{MEit\ x\ LEVit}) - (\ \mathrm{MEit} - 1\ \mathrm{x\ LEVit} - 1\ )}{(\mathrm{MEit} - 1)\ \mathrm{x}\ (\mathrm{LEVit}\ \ - 1)} \tag{1}$$

Where: ME = market value of bank's *i* total equity

LEV = is the bank's ratio of total assets to book equity.

Note that the total market value weighted sum of the X_t^i across all institutions gives the growth rate of market valued total assets for the financial system as a whole as applied within CoVaR.

To estimate CoVaR using quantile regression, we need 'state variables' (Tobias and Brunnermeier, 2016). This is because it allows us to capture the time variation in a joint distribution of returns for the system and individual institution. Therefore, making it possible to model the evolution of joint distributions over time. However, we are not to interpret these variables as systematic risk factors but rather as conditioning variables that are shifting the conditional mean and the conditional volatility of the risk measure. We restrict ourselves to a small set of state variables to avoid overfitting the data. Our state variables are:

(i) Short term '*liquidity spread*' defined as the difference between the three-month repo rate and the three-month bill rate. This measures short-term liquidity risk.

(ii) The *change in the three-month Treasury bill rate* from the Bank of England. We use this because the change, not the level, is considered as most significant in explaining the tails of financial sector market-valued asset returns.

(iii) The *change in the slope of the yield curve*, measured by the yield spread between the ten-year Treasury rate and the three-month bill rate obtained from the Bank of England.

(iv) The *change in the default spread*, measured as change in credit spread in 10-year BAA corporate bond and 10-year T-bond rate from the Bank of England.

(v) The quarterly market return computed from all share *FTSE index*.

(vi) The quarterly real estate sector return as measured by *FTSE UK Real Estate index returns*.

Other macro-control variables that have been included due to impact on market-valued total financial assets that could reflect the business cycle in the literature (e.g. Chen et al., 1986, Birz and Lott Jr, 2011, Cenesizoglu and Timmermann, 2008, Fama and French, 1993, Festic and Beko, 2009, Ludvigson and Ng, 2007, Petkova, 2006, Vassalou and Xing, 2003) are:

(vi) *Industrial production growth index*; measured by industrial growth index over industrial production index.

(viii) *GDP growth*; measured as the annual growth rate of GDP at market prices based on constant local currency.

(ix) *GDP per capita growth*; measured as gross domestic product divided by midyear population.

3.4.2 Bank level Variables:

The focus of this analysis is establishing the impact of recent regulations (Basel III and UK Independent Commission on Banking (ICB)) have had on systemic risk in the UK. To this end, bank-level variables that these regulations introduced or calculated differently are use as proxies to show the impact regulation is having on systemic risk indicator (ΔCoVaR). These consist of:

(i) **Bank Size**: Part of the recent regulation reduced the 'too-big-to-fail' phenomena that led to many financial institutions being bailed out with taxpayer resources, causing a huge public outcry. To mitigate the reoccurrence of such a situation, ICB put in place structural reforms and remove implicit guarantees that aim at reducing bank size. As in Laeven et al. (2016), we use the natural logarithm of a bank's *total assets* as proxy for bank size. Therefore, it serves as a proxy for 'too-big-to-fail'. We expect that the larger the relative size of a bank, the higher its contribution to systemic risk.

(ii) **Executive Pay**: The Financial Service Authority (FSA) identified potential market failures in the structures of remuneration practices in financial services. It suggested that an emphasis on short-term profits by institutional investors had encouraged executive remuneration to be focused on 'variable compensation' (bonuses) related to the most recent earnings, without any consideration of the exposure to risk-taking (Morgan and Robson, 2009). In addition, variable compensation schemes tend to be pro-cyclical since downside bonuses are capped at zero. In response to these perceived market failures, Treasury (2009) recommended a series of changes to remuneration practices: alignment of compensation and its risks made the responsibility of remuneration committees; transparency of the process and levels of executive pay; deferral of incentive payments; and performance criteria related to long-term profitability. These recommendations and eight key principles on executive remuneration are identified in Hall (2009) and enacted in an updated code for UK banks and building societies that became effective from January 2010. Consistent with this new regulation we use total executive pay to capture this regulatory change that is not limited to bonuses (e.g. stock-options that are tradinally perceived to increase risk). We use the growth of total senior executives' compensation that is measured by the total compensation paid to all senior executives. It acts as a proxy for reducing moral hazards associated with senior executive pay. It is expected to have a positive relationship with systemic risk.

(iii) **Ring-Fencing**: Ring-fencing is broadly designed to focus a bank on its traditional interest-generating retail and wholesale financial intermediation activities, such as deposit-taking and consumer/commercial lending. With non-core or non-traditional activities shifted into non-bank subsidiaries. Part of the main objectives of ring-fencing banks is to isolate retail-banking activities that are deemed essential and still have deposit insurance cover to continue operating even in difficult financial situations. Saunders et al. (2016a) show that Interest Income represents income received from all earning assets such as loans and investment securities.

It includes but is not restricted to; Interest and fees on loans, Interest on federal funds, Interest on bank deposits, along other interest-earning instruments. This serves as a proxy for ring fence activities of the banking group that has deposit insurance support. Bostandzic and Weiß (2018) also used interest income to capture ‘ring fenced’ banking activities and ‘non-interest income’ to represent activities outside the fenced banks are have been deemed more risky, such as investment banking.

(iv) **Non-Ring-Fence Activities**: DeYoung and Roland (2001) stated; non-interest income is more volatile than stable interest-income activities. Brunnermeier et al. (2012) show that banks with higher non-interest income have a higher contribution to systemic risk. The authors trace this notion back to the fact that non-core banking activities like, e.g., investment banking, is different from the traditional deposit-taking and lending functions of banks. Non-Interest Income represents all other operating revenues of the bank besides interest income that core ring-fenced banks do not carry out, instead done as part of ancillary services within the banking group (non-ring fence). It includes but is not restricted to; Investment securities gains/losses, Trust & fiduciary income, Commission & fees, Income from trading accounts, Foreign exchange income Banks, Other Financial Companies. Therefore, non-interest income serves as a proxy for non-ring fence activities of the banking group that has been deem more risky.

(v) **Regulatory Capital**: The newly introduced Total Capital Ratio represents the value of total net capital sources of financing available to a bank or a financial institution, calculated in accordance with Basel III accords. It is also be referred to as total regulatory capital; a high-quality buffer aims to absorb losses during periods of economic distress. It is aimed at improving stability and reducing the probability and impact of systemic financial crises in the future. It is to maintain the efficient flow of credit to the real economy and the ability of households and businesses to manage their risks and financial needs over time; and to preserve the functioning of the payments system and guaranteed capital certainty and liquidity for small savers, including small and medium-sized enterprises (Vickers, 2011).

(vi) **Leverage ratio:** This represents the ratio of Tier 1 capital to total risk exposure, used to estimate risks arising from the leverage of a financial institution's assets, expressed as a %. This ratio is a proxy for the level of a banks solvency. Total risk exposure includes the sum of all on-balance sheet exposures such as; gross loans, derivative exposures, securities financing transaction exposures and off-balance sheet exposures. This was calculated differently prior to the implementation of Basel III using the total asset to common equity to capture leverage.

Weiß et al. (2014) shows that a bank can become systemically important simply if its leverage is too high as losses during a stressed market situation could quickly cause such a bank to become undercapitalized. Brunnermeier et al. (2012) as well as Beltratti and Stulz (2012) confirm hypotheses that highly levered banks contribute more to systemic risk and performed worse than lower levered banks during the recent financial crisis. These findings are also underlined by Shleifer and Vishny (2010) who confirm that highly levered banks do not only contribute more to systemic risk, but also to higher economic volatility.

Table 3.1: Panel Summary statistics 2000-Q1 – 2019-Q4.

Variable	Obs	Mean	Std.Dev.	Min	Max	kurtosis	Skewness
Senior Executi~pay	535	17.321	1.051	15.000	22.00	4.411	1.301
Total Asset	610	19.001	2.511	14.001	25.213	1.911	-0.541
Total Capital Ratio	575	4.401	1.000	1.801	5.006	3.501	-1.053
Non-Interest Inc.	607	13.011	1.801	4.601	17.114	4.122	-0.782
Interest Income	591	14.514	1.601	3.221	16.109	3.002	-0.753
Leverage Ratio	590	3.100	0.914	-0.914	6.312	4.132	-0.422

Notes:Descriptive statistic of quarterly regulatory-targeted variables use for bank-level panel data regression. The table presents bank-specific balance sheet and income statement variables of UK banks covering the 2007 financial crisis period, regulation announcement and compliance window. The data are taken from the Thomson Reuters Financial DataStream and Thomson Worldscope databases. Absolute balance sheet and income statement items are given in $\$$ billion while ratios are given in per cent.

The mean value of *Total Asset* has the highest mean value within all panel variables, while *Leverage Ratio* (3.1%) has the lowest mean value. This is consistent with bank-level data, where there is a drive to increase assets and reduce the cost of financial investments. The standard deviation of Total Asset is also the highest, reflecting volatility that resulted from the crisis that affected banking assets more than all the other variables. Normally distributed data are assumed to have a symmetrical distribution around the mean, implying zero skewness. Thus, datasets with skewness deviating from zero deviate from a normal distribution. In Table 3.1, skewness is negative for all variables except the Senior Executive Pay, which has a positive skewness. Negative skew means the distribution has a longer left tail, meaning greater probability of tail risk that is consistent with empirical evidence of the crisis. Whereas, the positive skewness of Senior Executive Pay is consistent with the rationale provide by Morgan and Robson (2009) earlier discussed, and further shows the rationale why we included this variable within the analysis.

Kurtosis with values above three indicates leptokurtosis in the data distribution. Meaning, the distribution has a higher peak and fatter tails than the normal distribution. Further, this implies that more of the variance in the data is due to extreme deviations from the mean than would be the case if the distributions were normally distributed. Kurtosis from Table 1 supports the evidence data has fat tails. As pointed out by Engle (2004), kurtosis from real data sample is mostly above 3, which is the evidence of substantial extremes not suitable with normal random variables.

Finally, our dataset has an unequal number of observations amongst variables. Total Asset having the highest number of observations. In order to overcome the issue of missing data in our panel, we use the multiple imputations (mi) method. It was derive using the Bayesian paradigm that is shown to be statistically valid from the frequentist (randomization-based) perspective. This method used the definition from Rubin (1996) of statistical validity that implies approximately unbiased point estimates and implies confidence intervals achieving their nominal coverages when averaged over the randomise distributions induced by the known sample. The posited missing-data mechanisms used allows parameter estimates to be unbiased and the uncertainty of parameter estimation in the missing data case to be estimated in a reasonable way (see Roderick et al. (2002) and Allison (2001)).

3.5 Methodology

The measure of systemic risk applied is; delta CoVaR (ΔCoVaR) as developed by Adrian and Brunnermeier et al. (2012) and Adrian and Brunnermeier (2011). It is based on theoretical research on externalities across financial institutions that amplify liquidity spirals and persistent distortions. It also relates closely to recent econometric work on contagion and spillover effects. ΔCoVaR captures conditional tail-dependency

3.6 CoVaR

To understand ΔCoVaR, we need to go back to a common measure of risk use by banks, i.e. the value-at-risk 'VaR'. The VaR focuses on the risk of individual banks. It provides the confidence level 'q%' that a bank will lose at most in a period. VaR does not tell us the risk for the complete financial system i.e. systemic risk. However, the risk of a certain institution or herd of banks can potential spillover to other institution and leave the system at risk. To understand this, we look at conditional variance (CoVaR). Where institution *i*'s CoVaR relative to the whole system is defined as the VaR of the financial sector conditional on institution *i* being in a particular state. Making the systemic risk measure (ΔCoVaR), the difference between the CoVaR conditional on the distress of an institution and the CoVaR conditional on the median state of that institution.

Essentially, ΔCoVaR measures the component of systemic risk that co-moves with the distress of a particular institution. That is, the systemic risk measure associated with institution's *i,* ΔCoVaR^i, differs from that institution's own risk measure, VaR^i. Therefore, systemic-risk regulation should be base how individual risk affects the financial sector – a macro, outlook as oppose to individual risk factors only.

The application of CoVaR within empirical analysis is recent, however unlike other literatures, where estimation is via either quantile regression or Garch models, we have estimated CoVaR using both models and then applied 3 different accuracy tests of; Kupiec (1995); Christoffersen and Pelletier (2004); and Lopez (1999) in adopting the more accurate model for our analysis.

3.6.1 Estimating CoVaR via Quantile Regression

We stated that, $\mathrm{Var}^{i}_{q,t}$ is implicitly defined as the $q\%$ quantile, at time t, i.e.

$$\Pr\left(X^{i} \leq \mathrm{VaR}^{i}_{q,t}\right) = q\% \tag{3.1}$$

Where, X^{i}_{t} is the (return) loss of institution *i* for which the $\mathrm{Var}^{i}_{q,t}$ is defined at time t.

$\mathrm{CoVaR}^{j\,|C\,(Xi)}_{q}$ is referred to as the VaR of the financial system j conditional on some event $C\,(x^{i})$ of institution i. That is, $\mathrm{CoVaR}^{j\,|C\,(Xi)}_{q}$ is implicitly defined by the q% -quantile of the conditional probability distribution:

$$\Pr\left(Xj \mid C(Xi) \leq \mathrm{CoVaRq}\ j \mid C\ (Xi)\right) = q\% \tag{3.2}$$

Part of j's systemic risk (portfolio of all banks within the financial system) that can be attributed to institution *i* is then captured by;

$$\Delta\mathrm{CoVaR}^{j|i}_{q,t} = \mathrm{CoVaR}^{j|Xi=\mathrm{VaR}^{i}_{q}}_{q,t} - \mathrm{CoVaR}^{j|Xi=\mathrm{VaR}^{i}_{50}}_{q,t} \tag{3.3}$$

Note for specification above, j will be the financial system (i.e., portfolio consisting of all publicly trading banks in our universe (UK). It is important to remember at this point that to obtain CoVaR we condition on an event C that is equally likely across institutions. Usually C is institution *i* 's loss being at or above its VaR^{i}_{q} level, which, by definition, occurs with likelihood (1 − q) %. Importantly, this implies that the likelihood of the conditioning event is independent of the riskiness of *i*'s business model. It then follows that ΔCoVaR captures the change in CoVaR as one shifts the conditioning event from the median return of institution *i* to the adverse VaR_q^i.

To see the attractiveness of using quantile regression, consider the predicted value of a quantile regression of financial sector losses X_j^q on the losses of a particular institution *i* for the q% -quantile,

$$\widehat{X}^{system|Xi} = \widehat{\propto} + \widehat{\beta} X^i \tag{3.4}$$

Where, $\hat{X}_q^{j \mid Xi}$ denotes the predicted value for a q%- quantile of the system conditional on a return realization X^i of institution i. From the definition of value at risk, it follows directly that $\mathrm{CoVaR}^{j|Xi} = X_q^{j|Xi}$

That is, the predicted value from the quantile regression of system return losses on the losses of institution *i* gives the value at risk of the financial system conditional on X^i. The $\mathrm{CoVaR}_q^{j|i}$ given X^i is the conditional quantile. Using the predicted value of X^i = VaR_q^i yields the CoVaR_q^i measure ($\mathrm{CoVaR}_q^{j|i} = \mathrm{VaR}_q^i$). More formally, within the quantile regression framework, our $\mathrm{CoVaR}_q^{j|i}$ measure is given by:

$$\mathrm{CoVaR}_q^{j|i} = \mathrm{VaR}_q^{j|Xi=VaRiq} = \hat{\propto} iq + \beta \mathrm{VaR}_q^i \tag{3.5}$$

VaR^i can be obtained simply as the q% - quantile of institution *i*'s losses. So $\Delta\mathrm{CoVaR}_{q,t}^i$ is

$$\Delta\mathrm{CoVaR}_{q,t}^i = \mathrm{CoVaR}_{q,t}^i - \mathrm{CoVaR}_{q,t}^{i|VaRi50} = \beta_{q,t}^i \left(\mathrm{VaR}_{q,t}^i - \mathrm{VaR}_{50,t}^i\right) \tag{3.6}$$

3.6.2 Estimating CoVaR via Garch

Above equations (3.1 to 3.6) allows us to analyse systemic risk using state variables over time. We also follow the work of Girardi and Ergün (2013), to estimate CoVaR using GARCH model to obtain the time varying covariance between an institution and the financial system. As above, we use the portfolio of all UK banks as proxy for the financial system.

The estimation process is done in 3 stages. In stage 1, we start with the VaR for each institution that is computed by estimating the model:

$$X_t^i = \mu_t^i + \epsilon_{i,t} \tag{3.7}$$

Where;

$$\mu_{i,t} = \propto 0 + \propto 1 X_{t-1}^i;$$

$$_{i,t} = \zeta_{i,t} \sigma_{i,t},$$

$\zeta_{i,t}$ is i.i.d with zero mean and unit variance and the conditional variance has the standard GARCH (1,1) specification

$$\sigma_{i,t}^2 = \beta_i 0 + \beta_i 1\ \epsilon_{t-1}^2 + \beta_i 2\ \sigma_{i,t-1}^2 \tag{3.8}$$

In stage 2, for each institution *i,* we estimate the bivariate GARCH model with Engle's (2002) DCC specification for the returns (X^i) and the financial system (X^j).

Let $X_t = (X^i, X^j)$ whose joint dynamics be given by

$$X_{i,t} = \mu_t^i + \epsilon_{i,t},\ and\ \epsilon_{i,t} = \epsilon_t^{1/2}\ \zeta t \tag{3.9}$$

Where Σ_t is the (2 x 2) conditional covariance matrix of the error term $\epsilon_t \mu_t$ is the (2 x 1) vector of conditional means.

The standardized innovation vector $Z_t = \Sigma^{\frac{1}{2}} (Xt - \mu t)$ is i.i.d.

$$\Sigma\ (zt)\ =\ 0$$

And $Var_{z_t} = I_2$

We define D_t to be the (2 x 2) diagonal matrix with the conditional variances $\sigma^2_{x,t}$ and $\sigma^2_{y,t}$ along the diagonal so that $\{Dxx\}_t = \{\Sigma xx\}_t$, $\{Dyy\}_t = \{\Sigma yy\}_t$, and $\{Dxy\}_t = 0$ for x, y = s, j.

The conditional variances are then modelled as GARCH (1,1).

$$\sigma^2_{x,\ t} = \theta^x_0 + \theta^x_1\ \epsilon^2_{x,\ \ t-1}\ \theta^x_2\ \sigma^2_{x,\ t-1,} \tag{3.10}$$

$$\sigma^2_{y,\ t} = \theta^y_0 + \theta^y_1\ \epsilon^2_{y,\ \ t-1} + \theta^y_2\ \sigma^2_{y,\ t-1} \tag{3.11}$$

The conditional covariance $\sigma_{xy,t} = \rho_{xy,\ t}\ \sqrt{\sigma^2_{x,t}\sigma^2_{y,t}}$

Let $C_t = D^{-1/2}{}_t\ \Sigma_t D^{-1/2}{}_t = \{\rho xy\}_t$ be the (2 x 2) matrix of conditional correlations of ϵ_t. Following Engle (2002) we specify the conditional correlation matrix as follows

$$C_t = \text{diag}\ Q_t^{-1/2}\ \text{x}\ Q_t\ \text{x diag}\ Q_t^{-1/2} \tag{3.12}$$

$$Q_t = (1 - \delta_1 - \delta_2)\ \overline{Q} + \delta_1\ \ (U_{t-1}U'_{t-1}) + \delta_2\ Q_{t-1} \tag{3.13}$$

Where $\overline{Q}$ is the unconditional covariance matrix of $U_t = \left\{\frac{\epsilon_{\ x,t}}{\sigma_{x,t}}\right\} x = s, j$ and $\text{diaq}(Q_t)$ is the (2 x 2) matrix with the diagonal of Q_t on the diagonal and zeros off-diagonal.

At stage 3, we estimate the bivariate density, $\mathrm{pdf}_t(X_t^i;X_t^j)$ for each $X_t = (X_t^i;X_t^j)$ pair in step 3.11. We proceed to obtain our $\mathrm{CoVaR}_t^{J|Xi}$ measure for each financial institution *i* and time period t. Given the definition of CoVaR in Eq.3.5, it follows that;

$$\Pr\left(X_t^j \leq \mathrm{CoVaR}_{q,\,t}^{j|i} \,\middle|\, X_t^j \leq \mathrm{VaR}_{q,\,t}^{i}\right) = q, \tag{3.14}$$

$$\frac{\Pr\left(X_t^j \leq \mathrm{CoVaR}_{q,\,t}^{j|i} \mid X_t^j \leq \mathrm{VaR}_{q,\,t}^{i}\right)}{\Pr\left(X^j \leq \mathrm{VaR}_{q,\,t}^{i}\right)} = q. \tag{3.15}$$

Therefore, by definition of $\mathrm{VaR}_{q,\,t}^{i}$, $\Pr\left(X^j \leq \mathrm{VaR}_{q,\,t}^{j}\right) = q$. This means;

$$\Pr\left(X_t^j \leq \mathrm{CoVaR}_{q,\,t}^{j|i} \,\middle|\, X_t^j \leq \mathrm{VaR}_{q,\,t}^{i}\right) = q^2. \tag{3.16}$$

If we let $x,\ y = i,j$ given the $\mathrm{VaR}_{q,\,t}^{j}$ estimates obtained in stage 1, we can numerically solve the following double integral for $\mathrm{CoVaR}_{q,\,t}^{j|i}$

$$\int_{-\infty}^{\mathrm{CoVaRq\ j|it}} \int_{-\infty}^{\mathrm{VaRiq,t}} .\ \mathrm{pdf}_t\,(x,y)\,dydx = q^2 \tag{3.17}$$

In order to compute $\mathrm{CoVaR}_{q,\,t}^{j|i}$ we follow the same three-step procedure. The joint probability is then defined by:

$$\Pr\left(X^j \leq \mathrm{CoVaR}_{q,\,t}^{j|i},\ \mu_t^j - \sigma_t^j \leq X_t^j \leq \mathrm{VaR}_{q,\,t}^{j}\right) = p_t^j q. \tag{3.18}$$

The double integral solution therefore becomes

$$\int_{-\infty}^{\mathrm{CoVaRq}\ \mathrm{j|it}} \int_{-\infty}^{\mathrm{VaRiq,t}} .\ \mathrm{pdf}_t\,(x,y)\,dydx = p_t^j q^2. \tag{3.19}$$

As stated earlier, previous literatures have use either of the two methods above to obtain CoVaR. Whichever one was adopted in the main analysis, the other tends to be use for robustness of results obtained. However, what is done differently here is applying robustness checks on results obtained from QR and Garch (1,1) by using standard Kupiec (1995), Christoffersen (1998) and Lopez (1999). This allows our analysis to establish the more accurate model.

3.7 Backtesting

Backtesting is an important part of the Value-at-Risk model evaluation process (Ragnarsson, 2011). It takes the values calculated by the selected model and tests if the model has been accurate enough to justify its use on a given portfolio. Using the definition of CoVaR from equation 3.5, allows us to test the accuracy of quantile regression and Garch models to establish the more accurate model for our data set. We use Kupiec (1995); Christoffersen and Pelletier (2004); and Lopez (1999) tests to establish our result.

3.7.1 Kupiec Test

This is an unconditional coverage test and it measures whether the number of violations (when actual loss exceeds expected loss) is consistent with the chosen confidence level. The number of exceptions follows the binomial distribution and it is a hypothesis test, where the null hypothesis is:

$$H_0:\ p = \widehat{p} = \frac{x}{T} \tag{3.20}$$

Where p represents the violation rate from the chosen Value-at-Risk level, $\hat{p}$ represents the observed violation rate and x represents the number of observed violations. T is the number of observations. It is conducted as a likelihood-ratio test (LR test) and formulated as:

$$LR_{UC} = 2\ln\left(\frac{\widehat{p}^{x}\ \widehat{(1-p)}^{T-x}}{p^{x}\ (1-p)^{T-x}}\right),\ \widehat{p} = \frac{x}{T} \tag{3.21}$$

Therefore, under the null hypothesis test $\mathrm{LR_{UC}}$ is asymptotically chi-square distributed with one degree of freedom. If the $\mathrm{LR_{UC}}$ statistic exceeds the critical value, the null hypothesis is rejected and therefore the model seems inaccurate (Borges and Ragnarsson, 2011). Therefore, our alternative hypothesis becomes

$$\mathrm{H_1} = LR_{uc} \; > \; X^2. \tag{3.22}$$

3.7.2 Christoffersen Test

This is a test of violations, serial independence and conditional coverage. Like the Kupiec test, it collects data for violations and if they happen subsequently. The results from this data are used to create the test results. The observations can have two values as shown below.

$$\mathrm{I_t} = \begin{cases} 1, & \text{if violation occurs} \\ 0, & \text{if no violation occurs} \end{cases}$$

These results are categorized in the following manner: if there was a violation followed by non-violation, a non-violation followed by a violation, a non-violation followed by a non-violation and a violation followed by a violation, as shown below:

Table 3.2: Violation matrix

	$I_{t-1} = 0$	$I_{t-1} = 1$	
$I_t = 0$	n_{00}	n_{10}	$n_{00} + n_{10}$
$I_t = 1$	n_{01}	n_{11}	$n_{01} + n_{11}$
	$n_{00} + n_{01}$	$n_{10} + n_{11}$	

Notes:Test table that captures how violations are categorized as explained above. Where n_{00} = non violation followed by non-violation, n_{01} = non-violation followed by violation, n_1 = violation followed by non-violation and n_{11} = violation followed by violiation.

From table 3.2 above, values for π_0 and π_{01} are calculated. They represent the sample probabilities of a violation occurring conditional on the presence or absence of violation in the previous day. π is then calculated and it represents the violation rate, as shown below:

$$\pi_0 = \frac{n_{01}}{n_{00} + n_{01}}, \pi_1 = \frac{n_{11}}{n_{10} + n_{11}}, \pi = \frac{n_{01} + n_{11}}{n_{00} + n_{10} + n_{10} + n_{11}} \tag{3.23}$$

The likelihood-ratio test is calculated under the null-hypothesis that all violations should be independent of each other. The null-hypothesis takes the form:

$$H_0 : \pi_0 = \pi_1$$

The likelihood statistics is calculated as:

$$\mathrm{LR_{ind}} = -2\ln\left(\frac{1-\pi^{\ n_{00}+\ n_{10}} \quad \pi^{n_{00}+\ n_{10}}}{(1-\pi_0)^{n_{00}} \ \ \pi_0{}^{n_{01}}\ (1-\pi_1)^{n_{10}}\ \pi_1{}^{n_{11}}}\right) \tag{3.24}$$

This is asymptotically chi-square distributed with one degree of freedom.

If the test statistics is above that value, the null hypothesis is rejected, and the model is considered to have independence problems. Therefore, our alternative hypothesis becomes:

$$H_1 : \ \mathrm{LR}_{\mathrm{ind}} > \ X^2.$$

A test statistic under the critical rate assumes the model to be better (Nieppola, 2009). Christoffersen further created a joint test consisting of the previously described tests for unconditional coverage and for independence. The test statistic is as follows:

$$LR_{cc} = LR_{uc} + LR_{ind} \tag{3.25}$$

Please note: test for unconditional coverage and Christoffersen test for independence are summed to get the test results for conditional coverage. The test for conditional coverage is also asymptotically chi-square distributed and has two degrees of freedom. Making the model pass the test if its test statistic is under the critical value (Christoffersen & Pelletier, 2004).

3.7.3 Lopez loss function

This is neither an independence test nor a test for unconditional coverage. It looks at the losses made when there is a violation and by how much the losses exceed the projected Value-at-Risk number. Every observation gets a value, similar to the independence test where every violation got a value of one otherwise zero. For observations with no violation the value is set at zero, alternatively when there is a violation the value is one plus the magnitude of the exceedance squared. As shown below:

$$\mathrm{L}(VaR_t\ (\propto),\ r_t = \begin{cases} 1 + (r_t + \ VaR_t\ (\propto))^2, & \text{if violation occurs} \\ 0, & \text{if no violation occurs} \end{cases} \Big\} \tag{3.26}$$

Where $VaR_t\ (\propto)$ represents the projected Value- at-Risk number for time *t*, $\propto$ represents the

chosen confidence level and r_t is the observed return at time *t*. To get a single value, the results are calculated using the following formula:

$$\hat{L} = \frac{1}{T} \sum_{t=1}^{T} \mathrm{L}(VaR_t\ (\propto),\ r_t) \tag{3.27}$$

Note that there are some shortfalls with the Lopez Loss function since the returns' actual distribution is unknown. It is also hard to know how much exceedance is actually appropriate and how much leads to a rejection of the model. Therefore, the Loss function serves as a good remedy for comparing different models to establish some extraordinary exceedances prevailing (Lopez, 1999).

Finally, to establish the impact of regulatory variables, we use panel regression that takes a form of

$$\Delta \mathrm{CoVaR}^{\mathrm{i}}_{\mathrm{j,\ t}} = \beta_0 + \beta \mathrm{B}^{ij}_{t} + \epsilon_{it} \tag{3.28}$$

where $\Delta \mathrm{CoVaR}^{\mathrm{i}}_{\mathrm{q,\ t}}$ is a measure of risk of bank *i* within system j, computed over period t, β_0 is the panel fixed effect, $\beta^{\mathrm{ij}}{}_{t}$ is a vector of bank characteristics computed at time, and $\epsilon_{i,t}$ is the error term. We use lags of these variables to correct for endogenous risk persistence. Please note, all explanatory variables are standardized to have zero mean and unit standard deviation in all the panel regressions. An estimated coefficient thus represents the effect of a one standard deviation increase in the explanatory variable on the systemic risk measure.

3.8 Empirical Results

Our analysis builds on previous work undertaken by Tobias and Brunnermeier (2016). What is different here is that we start by calculating panel VaR and system CoVaR using both quantile regression and Garch models. Using the results[1] from both methods, we performed backtesting analysis using Kupiec (1995), Christoffersen (1998) and Lopez (1999) tests in order to establish which of the two estimation method is more accurate for our dataset. Whereas most of the literature in this area focus on individual banks contribution to systemic risk, the focus of this analysis is the impact regulatory target variables have had on systemic risk, to this end we use ran panel regression to establish this relationship.

Our analysis start by calculating quarterly VaR$_{95}$ and VaR$_{50}$ on panel of banks in our data from 2000 to 2019 with quarterly data. The result from this is then use to calculate CoVaR$_{95}$ and CoVaR$_{50}$. The four results are then used for accuracy tests as presented below. Table 3.3 present our initial accuracy test results from VaR and CoVaR calculations.

[1] See appendix for estimation results.

Table 3.3: Kupiec test of Violation results

	Panel VaR - QR	Panel VaR - Garch	CoVaR - QR	CoVaR - Garch
5% signifance				
n1	93	9	37	9
n0	454	538	511	539
q	0.050	0.050	0.050	0.050
pi	0.170	0.016	0.067	0.016
LR1	15.009	17.333	3.205	1.403
p-value	1.224	3.145	0.073	3.025

Note:summary of our unconditional coverage tests. It shows the accuracy of VaR and CoVaR models estimated from QR and Garch models using 5% level of significance.Where n_0 = non violation and n_1 = number of violations.

Comparing the p-values and likelihood ratio (LR1) figures from the table shows that both models are acceptable, although accuracy from the Garch model is better when looking at Panel VaR calculation. Results show the QR model is more accurate in dealing with CoVaR analysis. A plausible explanation for this may be due to the fact that QR takes into consideration 'state variables' when analysing CoVaR, therefore factoring in other variables that capture the relationship between institutions and their impact on these conditional risk relationship. By conditioning on another institution's financial distress, CoVaR goes beyond idiosyncratic risk and captures possible risk spillovers among financial institutions. Therefore, further supporting our choice of methodology.

Table 3.4: Christoffersen test of independence

	Panel VaR - QR	Panel VaR - Garch	CoVaR - QR	CoVaR - Garch
5% signifance				
n00	400	528	481	533
n01	54	9	30	5
n10	53	9	29	5
n11	39	0	7	4
pi01	0.118	0.016	0.058	0.009
pi11	0.423	0.000	0.194	0.004
pi2	0.170	0.0164	0.067	0.016
LR2	41.747	0.301	6.979	22.680
p-value	0.582	0.804	0.924	0.008

Note:This test produces result that takes into consideration volatility clustering in order to avoid serial correlation in the violation sequence.Where n_{00} = number of non violation followed by non-violation, n_{01} = number of non-violation followed by violation, n_1 = number of violation followed by non-violation and n_{11} = number of violation followed by violiation..

Our result supports the accuracy of the Garch estimation method over QR when calculating the VaR of individual banks. Tobias and Brunnermeier (2016) also show that showed Garch estimates perform better for the ninety-fifth percentile, while the quantile estimates perform considerably better for the ninety-ninth percentile. Our result supports the idea that; the QR is a more parsimonious measure of systemic risk that captures the tail-dependency between an institution and the financial system as a whole (White et al., 2015).

Table 3.5: Christoffersen conditional coverage test result.

	Panel VaR - QR	Panel VaR - Garch	CoVaR - QR	CoVaR - Garch
5% signifance				
LR3	46.756	17.635	10.184	40.081
p-value	0.001	0.363	0.981	0.006

Note:It is a combination of unconditional and independence tests above. The test for conditional coverage is also asymptotically chi-square distributed and has two degrees of freedom. The critical value at 95% confidence level is 5.99. Making the model pass the test if its test statistic is under the critical value (Christoffersen and Pelletier, 2004).

It also follows the same trend, supporting the accuracy of Garch over QR when testing on VaR and vice versa when considering CoVaR. Finally, we ran the Lopez loss function. The results in Table 3.5 below are also in line with all previous accuracy test. That is panel VaR using Garch more produce a better model, while QR model produces more accuracy with CoVaR.

Table 3.6: Lopez test result

	Panel VaR - QR	Panel VaR - Garch	CoVaR - QR	CoVaR - Garch
5% signifance				
Violation Ratio (G)	0.170	0.016	0.067	0.016
Lopez (L)	0.183	0.016	0.067	0.029
Difference (L – G)	0.013	0.000	0.000	0.013

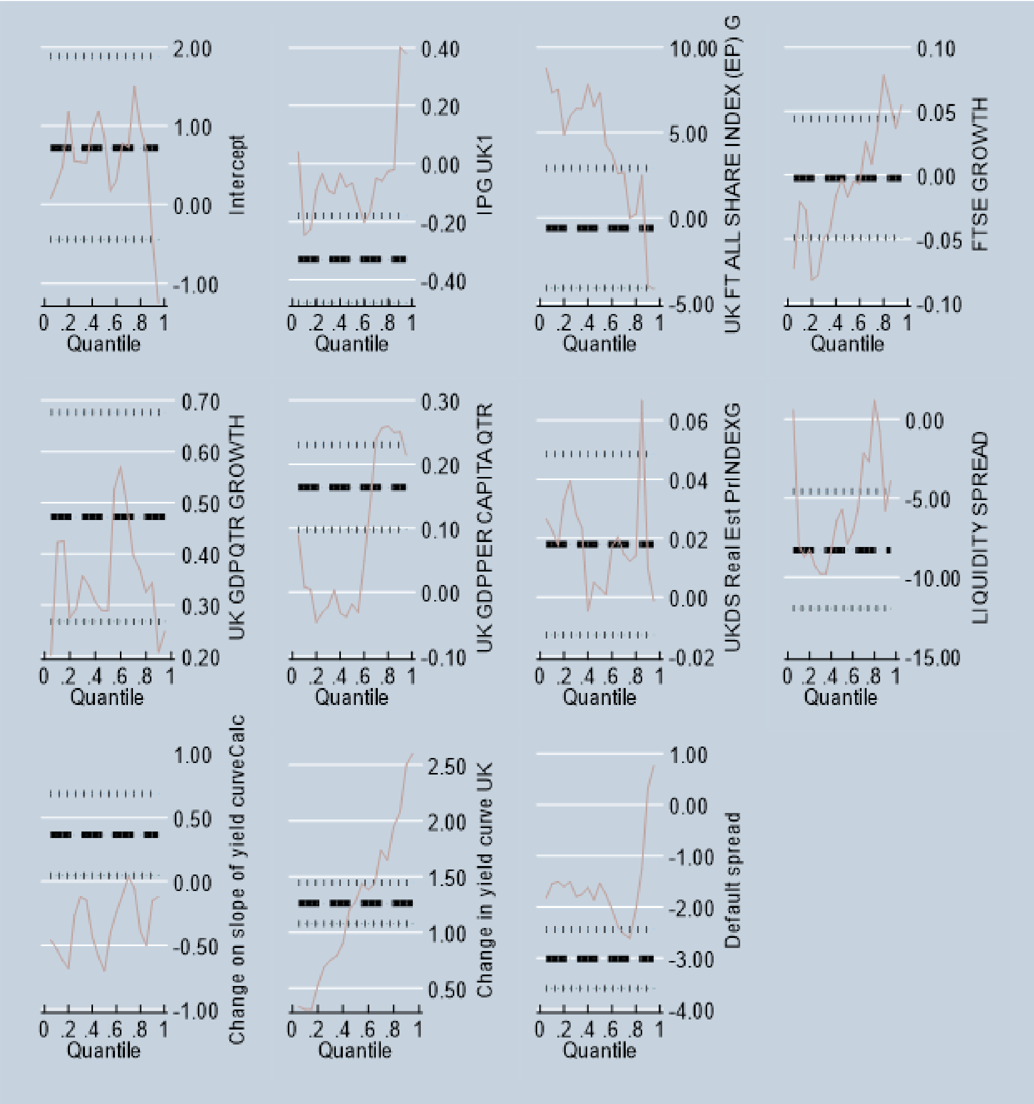
Note:It looks at the losses made when there is a violation. It also provides the more accurate model using the least (L-G) difference.

Brunnermeier et al. (2012) also stated that QR are a more efficient way to estimate CoVaR. Given the results from our accuracy tests, the rest of this analysis therefore correctly uses QR for calculating ΔCoVaR that is use for panel regression in later part of this analysis.

3.8.1 Analysis of CoVaR using Quantile Regression (QR)

Given our datasets and accuracy test results, QR is more robust when applied to CoVaR. In order to further justifying the estimation of CoVaR using QR, it is important to establish that all state variables used are significantly different from an OLS regression at quantile of interest, in our case 5%. Figure 3.1 below shows that all coefficients and confidence interval of state variables use to estimate CoVaR have differential effects at different quantiles outside the OLS estimation and captures the time-varying tail behaviour of these variables that are important for systemic risk. It justifies the application of QR beyond capturing time variation in the conditional moments of asset returns and the existence of tail events that would be missed if average effects of state variables were considered on systemic risk variable. For example, the average impact of liquidity spread on CoVaR is -8%, whereas at 5% quantile it is -1%, showing different effects for outlier tail events.

Figure 3.1: Quantiles of state variables



Note: the black hard dash lines represent the OLS regression line and the slim lines around them represent the confidence intervals. The green lines however show the QR at different quantile intervals. All our variables show significant differential effects from OLS. Source: Author.

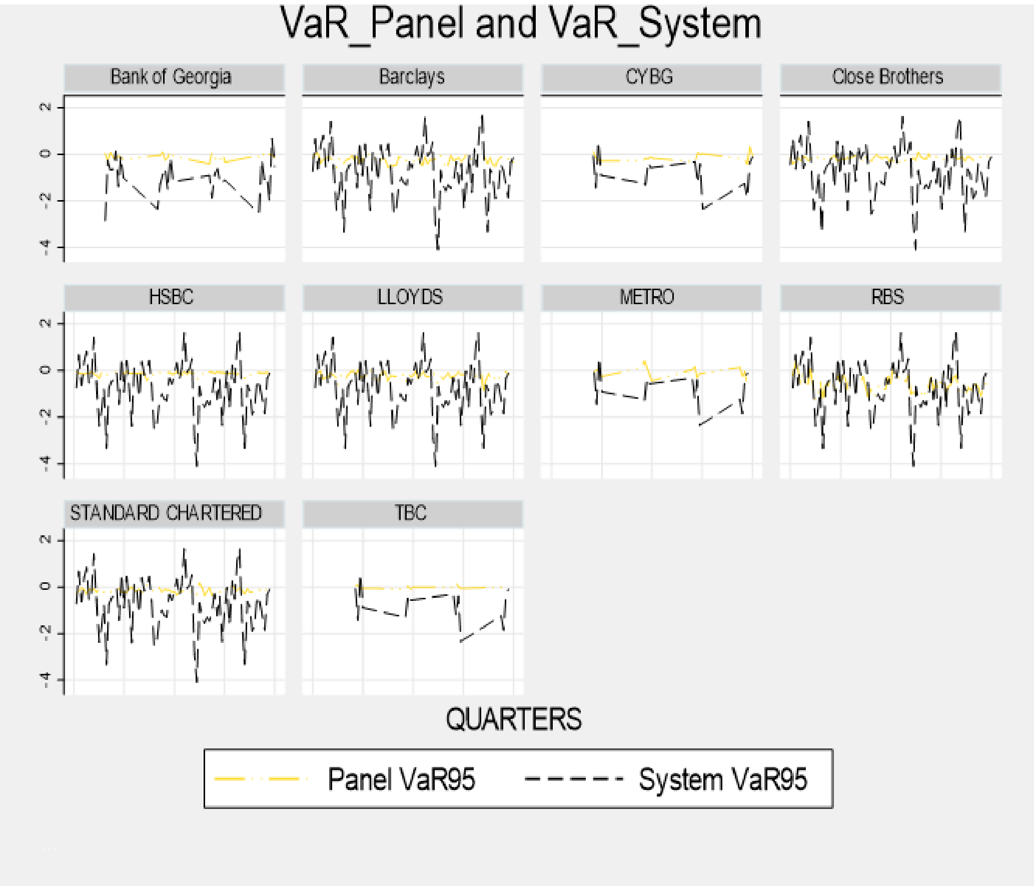
Table 3.7: Quantile Regression using state variables

$R^i{}_t$	QR^{05}	$R^i{}_t$	QR^{50}
Industrial Prod. Growth	0.117*** 0.000	Industrial Prod. Growth	-0.202 0.110
FTSE100 Growth	-0.068*** 0.111	FTSE100 Growth	0.026 0.500
GDP Growth	-0.120*** 0.000	GDP Growth	0.166 0.334
Per Cap Growth	0.034** 0.010	Per Cap Growth	0.036 0.517
Real Estate Growth	0.047*** 0.000	Real Estate Growth	-0.025 0.313
Liquidity Spread	-5.001** 0.000	Liquidity Spread	-7.729* 0.012
Yield Curve	-0.322*** 0.000	Yield Curve	-0.658* 0.000
Change in 3month T-bill	0.522*** 0.000	Change in 3month T-bill	1.318*** 0.151
Default Spread	-1.707*** 0.000	Default Spread	-1.908*** 0.001
constant	1.033*** 0.000	constant	1.788 0.000
Pseudo R2 = 0.496		Pseudo R2 = 0.417	

Note:The Table shows the result of state variable when estimating QR at 5% and 50% significance level.

This is similar to the result from Tobias and Brunnermeier (2016). It shows at high percentile, QR captures tail risk more accurately (with all variables performing better).

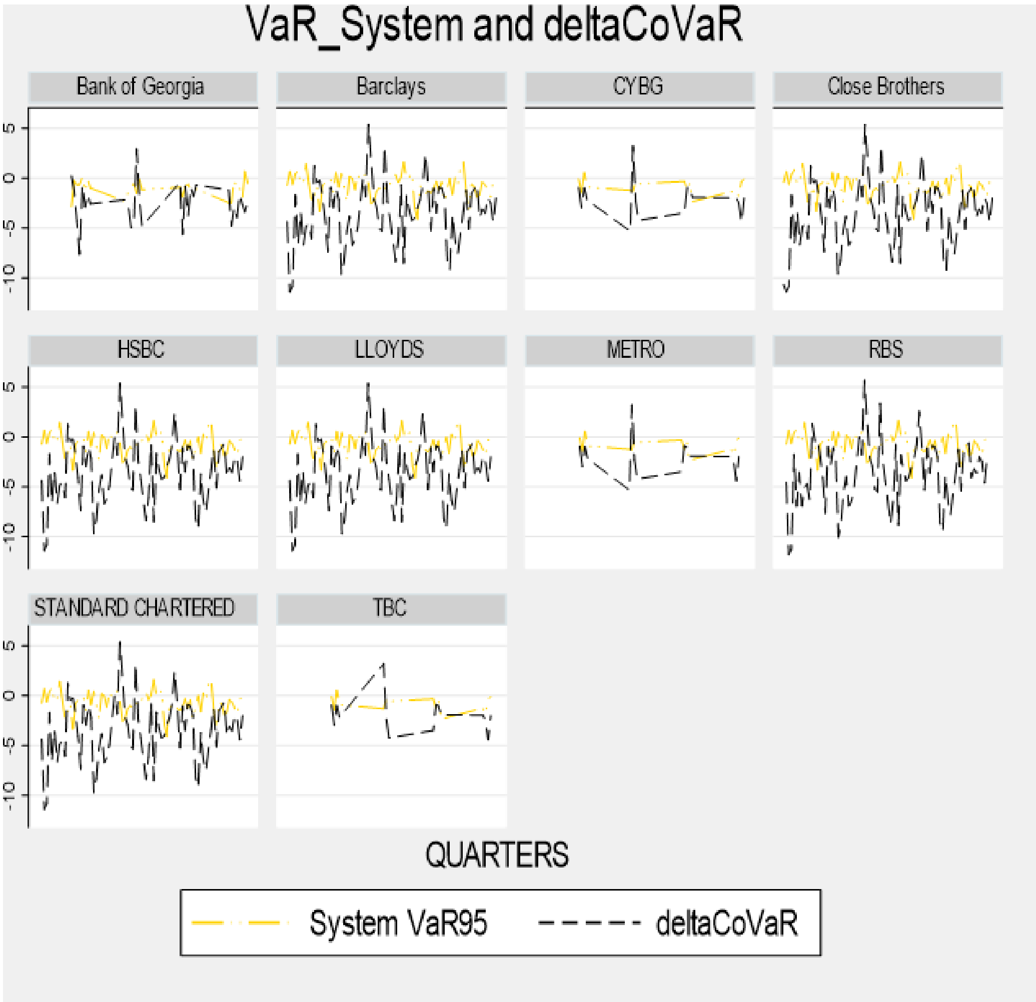
Figure 3.2: The movement of VaR and CoVaR over our whole sample period.



Note: Time series of VaR and CoVaR over the entire sample period of 2000 - 2019.Source:Author.

The plot for VaR time series for the panel shows a relatively stable pattern when compared to CoVaR plot over the same period. Hence, applying financial regulation solely based on the risk of an institution in isolation will not be sufficient to insulate the financial sector against systemic risk.

Figure 3.3: The movement of CoVaR (VaR_system) and ΔCoVaR (delta-COVAR) over our whole sample period



Note: These graphs highlight individual bank systemic risk contribution (ΔCoVaR) against the risk within banking system (CoVaR) for the period of 2000-Q1 – 2019-Q4. Source: Author.

It shows the plot of the time series ΔCoVaR against CoVaR for all institutions in our sample. It shows there is a strong time series relationship. Meaning, the contribution of each bank is closely related to movement of systemic risk within the system. This supports the change in regulation that is macro in outlook as opposed to the micro nature of regulation prior to the crisis.

Next, we discuss the main impact regulation is having on systemic risk in the UK. We use the result from above (ΔCoVaR) and relate it to a set of bank-specific variables in panel data regressions. We regress the values of the systemic risk proxy on six identified bank level regulatory variables using fixed effect panel regressions to account for unobserved heterogeneity across our sample banks and across time.

Table 3.8: Regression of ∆CoVaR against bank level variables

	(Complete sample period)	(Post-regulation sample)	(Pre-regulation sample)
Dependent Variable	∆CoVaR	∆CoVaR	∆CoVaR
Senior Exec. Compensation	0.036***	-0.262	0.627
	0.011	0.151	0.334
Total Asset	0.297**	-0.183**	-0.310
	0.022	0.041	0.931
Total Capital Ratio	-0.322**	-0.016**	0.315
	0.021	0.040	0.181
Non-Interest Income	0.168	0.082	0.299
	0.241	0.651	0.173
Interest Income	-0.127***	0.019	-0.090***
	0.000	0.122	0.000
Leverage	0.205	0.090**	-0.232*
	0.230	0.041	0.081
Dummy	-0.287***	-	-
	0.000	-	-
Constant	-	-2.586	-
	53.717***	0.850	53.748***
	0.000		0.000
Observations	888	480	488
R-squared	0.441	0.552	0.512

Note:Note: We estimate the regression ΔCoVaR = ατ + βSenior Executives Compensationit + βTotal Assetit + βTotal Capital Ratioit + βNon-Interest Incomeit + βInterest Incomeit + βLeverageit + βDummyit + εit to evaluate the impact regulation is having on systemic risk in the UK, using banks individual variables i, at time t , while εit is a Gaussian error term assumed to be uncorrelated with the regressors. from 2000 (Q1) to 2019 (Q4). To estimate the coefficients, we run 3 regressions that covers 3 different samples. The t-statistics in parentheses are computed using standard errors robust to heteroskedasticity and autocorrelation. Significance: *p < 0.10, **p < 0.05, ***p < 0.01.

Our results offers a number of interesting implications for UK regulatory bodies to reconsider its approach. Our panel regression consist of variables that combine regulatory changes in the UK and Basel III set out for banks to comply with from the time of announcement in 2010 to end of compliance period in 2019 (other than few parts that have been extended and not relevant for this analysis). We ran 3 different panel regressions. Regression 1 (Complete sample period) covers the whole sample, i.e. 2000-Q1 to 2019-Q4. Regression 2 (Post-regulation period) forms our main contribution to the literature. It covers the time-period from 2014-Q1 – 2019Q4, this is the regulatory compliance period by all banks on examined variables. Regression 3 (Pre-regulation period) covers the crisis period and time before the crisis, given us a good understand on the relationship of these variables with systemic risk leading up to the crisis. We refer to these different sample periods as regression 1, 2 & 3 for the remaining of this discussion.

Generally, our R squared for all 3 respective regressions (0.441, 0.552, and 0.512) are acceptable as other explanatory variables that likely impact systemic risk such as interconnectedness and bank concentration that have not been factored into the analysis. The reason being that there is no explicitly regulation within Basel III or the UK regulation that have tried to influence these variables directly. Although, UK regulation allows customers to switch bank accounts more easily in a bid to increase competition, this does not capture interconnectedness or level of concentration.

Basel III was announced in November 2010 and implementation started in January 2013. It also had an initial full compliance date of January 2019, however at the time of this analysis the date is extended to 2022 for some of the variables like the liquidity coverage ratio and net stable fund ratio. The earliest compliance date for a Basel III variable – The core capital ratios was January 2015. For this reason we use 'total capital ratio' to capture Basel III tier I and tier II capital requirement. King and Tarbert (2011) also stated these are arguably the most important aspect of the regulation. Although these ratios were phased in from the time Basel III was announce, and supervision by Basel committee for compliance started in 2011, empirical data show that Banks in the UK already meet this requirement before the end of 2010. Therefore, for empirical accuracy when analysing the impact of regulation, we choose 2014 as starting point for regulation as the data show that all banks where compliant with all the variables use in this analysis in 2013-Q2. Next we discuss variables used for this analysis.

Table 3.8 shows that Total capital ratio – a variable that captures the ability of banks to absorb losses during periods of economic distress has no statistical significance with respect to our systemic risk dependent variable – ΔCoVaR, for the period building up to the crisis (regression 3). This supports the effectiveness of the regulation and why capital ratio is made a priority. Regression 2 shows the expected nature of its relationship to systemic risk with statistical significance. It suggests that implementation of capital requirement has reduce to likelihood of banks not absorbing their losses and therefore reducing systemic risk by 0.016%.

Laeven et al. (2016) also find some evidence that systemic risk is lower in more-capitalized banks, with effects particularly more pronounced for large banks.

Basel III Leverage ratio introduction is a result of banks being able to show they had sufficient capital while holding excessive risk before the crisis (King and Tarbert, 2011) . It therefore serves as a reinforcing risk measure. It is important to remember here that Basel III leverage is also calculated by comparing Tier 1 capital with “total exposure,” without reference to RWAs (i.e. including off balance exposures). The overall target is a minimum of 3 percent. Our result show that the relationship of leverage ratio to systemic risk is positive at 0.09% before regulation and about -0.23% afterwards. This is an important difference as it shows that prior to implementation of regulation, higher ratio suggests more risk, while post regulation banks are expected to meet a minimum threshold and the further it is from the threshold the more risky it seem. Both results are statistically significant at 5% and 10% level respectively. Also, note the result of leverage ratio from the full regression is not significant, although it shows a positive relationship. This could result from the fact that Basel III leverage and normal leverage calculations and relationship are different. From a sample of international banks, López-Espinosa et al. (2012) concluded that leverage seem to provide little incremental information about systemic risk. This is similar to our full sample result, but significant different from our conclusion. An explanation could be that out analysis did factor in the changes of how leverage is calculated under the new rules and differentiate sample periods to account for these changes. Our data also factored in a reasonable amount of the new leverage ratio data that most studies have not use (an advantage due to how recent we collected the data).

In the UK, regulation of banks after the crisis went beyond Basel III requirements. As a package, UK regulation official announcement was made in September 2011. The most prominent of these being ring fencing of banks. We use interest income to capture this (as consistently done within the literature). Overall, regression 1 and 3 show that interest income has a negative relationship with systemic risk at 1% level of significance, reducing ΔCoVaR by about 0.13% and 0.09% respectively. However, regression 2 does not show the expected relationship or statistical significance. It shows that while this regulation can be econometrically justified prior to implementing the regulation, our analysis shows it has no impact on systemic risk. Therefore, UK regulatory agency should revisit the imposition of ring fencing on banks as our result does not support empirical economic justification. It highlights the need to insulate core-banking activities that can continuously access deposit insurance even during crisis. Others equally argue it reduces the benefits that come from diversification. Brunnermeier et al. (2012) also found that interest income marginally decreases systemic risk at the 10% level of statistical significance. Overall, neither the literature nor our analysis (after exclusively looking at the regulatory phase period) show that ring fencing as captured by interest income reduces systemic risk. Using a set of global banks, Bostandzic and Weiß (2018) find that the ratio of non-interest income to interest income ratio to be associated with a significant decrease in a bank's contribution to global systemic risk. They suggested from their result one could hypothesize that a more traditional business model does not necessarily stabilize the financial sector. Further supporting our findings on interest income.

We did not find any relationship with non-interest variable (this is the proxy to non-ring fence activities within banking group) and our systemic risk measure. The results from all 3 regressions are not statistically significant. Although, this may be attributed to the fact that our sample use only banks in the analysis and leaving out investment banks and other financial institutions that likely capture activities outside ring fence activities more accurately. However, Brunnermeier et al. (2012), find that the ratio of non-interest income to total assets is strongly positively correlated with ΔCoVaR, suggesting that non-interest income contributes adversely to systemic risk. On the other hand, like our result, Engle et al. (2014); Weiß et al. (2014); and Saunders et al. (2014) found no relationship between non-interest income and systemic risk. This mix results further questions the regulation of ring fencing and suggests room for future further research.

Gandhi and Lustig (2015); Bostandzic and Weiß (2018); Laeven et al. (2016); all used total asset as proxy to bank size in their analysis as adopted here. An important part of the regulation is making the system robust that government overcome the issue of 'too-big-to-fail' banks by not bailing them out as they did at the time of the crisis. While regression 3 does not show any relationship between size and systemic risk, both regression 1 and 2 have statistically significant results. That is banks size affected systemic risk at about 0.30% and -0.18% respectively. The results show different relationship signs. Suggesting that before regulation, size affected systemic risk positively and banks have reduce their size after regulation and as a result reduce their contribution to systemic risk, justifying the implementation of this regulation.

The variable of executive pay impacts risk of banks and therefore systemic risk at some level (Hubbard and Palia, 1995). The crisis questioned not only the justification that top executives are paid but the amount as well. Therefore, part of the regulation was to cap the amount top executives are paid and bonuses being paid using company shares. This is supposed to act as a proxy for reducing moral hazards that can contribute to systemic risk. Our regressions for before and after the implementation of regulation (regression 2 and 3) do not show any statistically significant results, although the signs of the relationship do suggest a positive relationship. However, the full regression from 2000-Q1 to 2019-Q4 show a statistically significant relationship that suggests top executive pay do have a relationship with systemic that is positive in nature. The result show that executive pay increases systemic risk by about 0.04%. Using data for US banks between 1992 – 2008, Guo et al. (2015) find that bank risk increases with both the %s of short-term and long-term incentive compensation. However, greater proportion of incentive pay decreases the likelihood for a bank to become a problem or failed institution. While, Palia and Porter (2004) find that the level of salary and bonus of CEO compensation is negatively related to bank risk, consistent with the theory of Kotter (2000), that bank risk (measured by the standard deviation of stock returns) decreases when managers' salary and bonus increase. Finally, we use a dummy variable to capture the overall effect of regulation within the whole sample period. The result shows that our dummy beta is significant with a co-efficient that is interpreted as the intercept shifting effect at around -0.287. Showing that the overall introduction of regulation within that period as reduced systemic risk as captured by ΔCoVaR by around 0.287%.

As a robustness check, we estimate ΔCoVaR using a GARCH model (DCC) and find that this method produces estimates quite similar to the quantile regression method, leading us to the conclusion that the quantile regression framework is sufficiently flexible to estimate ΔCoVaR.

3.9 Conclusion

During financial crises, tail events tend to spill across financial institutions. Such spillovers are preceded by a phase in which risk builds up. CoVaR is a parsimonious measure of systemic risk that captures the tail-dependency between an institution and the financial system as a whole. It broadens risk measurement to afford a macroprudential perspective in a cross-section and complements measures designed to assess individual financial institutions' micro-prudential risk.

Adopting the method from Adrian and Brunnermeier (2011), along with Garch (1,1) as used by Girardi and Ergün (2013), we calculated CoVaR of Banks in the UK for the period of 2000 – 2019. We build on the literature by applying accuracy tests that show QR is more efficient when estimating CoVaR as compared to a Garch model.

The analysis contributed to the literature by investigating some of the variables that are the focus of regulation after the financial crisis. We divided our sample to capture post and pre- regulatory periods by using announcement/compliance dates and as shown by the data. Our results present important findings to some of regulations implemented after the crisis period in the UK. The main one being ring fencing. Using interest income as a proxy for this regulation, our analysis show that this variable has no statistical significance in reducing systemic risk after regulation (as oppose to its statistical relevance in our pre-regulation regression analysis). This is further supported when we look at the result of our non-interest income (a proxy for non-ring fence activities) that was expected to increase systemic risk but showed no such relationship in the post-regulatory period. Thus, making us suggest that this policy needs further research in terms of its impact to systemic risk. As it could be harming the system, instead of reducing system risk as expected. Similar conclusion was reached by De Jonghe et al. (2015). They showed that from a systemic risk point of view, forcing banks to go back traditional activities is good only for small banks. On the other hand, systemic risk increases when large banks are ring-fenced. Equally, Engle et al. (2014); Weiß et al. (2014); and Saunders et al. (2014) found no relationship between non-interest income and systemic risk.

Our result show that measures taken to reduce bank size to be of statistical significance with an inverse relationship systemic risk. This is in line with results from Laeven et al. (2016), that find strong evidence that systemic risk increases with bank size. Allowing us to conclude that the effort by regulatory agency to reduce bank size is effective.

Finally, our results show that Basel III variables provide strong and valid justification in the attempts made by regulation to reduce systemic risk. It shows that more capitalised banks are better able to reduce systemic risk and the change in the way leverage ratio is calculated to further capture all off balance sheet items that potentially increase systemic is statistically significant. This is similar with the results of Berger and Bouwman (2013) who show that bank capital increases a bank's survival probability, showing that the increase in capital regulations reduces the exposure of banks to systemic risk.

3.10 Appendix

This Appendix explains how to use quantile regressions to estimate VaR and CoVaR. As discussed the model considered here is a special case of the stylized financial system analyzed in Section II, with particularly simple expressions for μ^j (*) , σ^{ji} (*), and σ^{jj} (*). Specifically, we assume that losses X_t^i have the following linear factor structure

$X^j_{t+1} = \phi_0 + \mathbf{M}_t\, \boldsymbol{\phi}_1 + X^i_{t+1}\, \phi_2 + (\phi_3 + \mathbf{M}_t\, \boldsymbol{\phi}_4)\, \Delta Z^j_{t+1}$ (4.1)

where $\mathbf{M}_t$ is a vector of state variables. The error term ΔZ^j_{t+1} is assumed to be i.i.d. with zero mean and unit variance, and $E[\Delta Z^j_{t+1} \mid \mathbf{M}_t + X^i_{t+1}] = 0$. The conditional expected return $\mu^j [X^j_{t+1} \mid \mathbf{M}_t, X^i_{t+1}] = \phi_0 + \mathbf{M}_t\, \boldsymbol{\phi}_1 + X^i_{t+1}\, \phi_2$ depends on the set of state variables $\mathbf{M}_t$ and on X^i_{t+1}, and the conditional volatility $\sigma^{jj}_t [X^j_{t+1} \mid \mathbf{M}_t, X^i_{t+1}] = (\phi_3 + \mathbf{M}_t\, \phi_4)$ is a direct function of the state variables $\mathbf{M}_t$. The coefficients ϕ_0, ϕ_1, and ϕ_2 could be estimated consistently via OLS of X t i+ 1 on **M** t and X t i+ 1. The predicted value of such an OLS regression would be the mean of X^j_{t+1}conditional on $\mathbf{M}_t$ and X^i_{t+1}. In order to compute the VaR and CoVaR from OLS regressions, one would have to also estimate ϕ_3, and ϕ_4, and then make distributional assumptions about ΔZ^j_{t+1}. The quantile regressions incorporate estimates of the conditional mean and the conditional volatility to produce conditional quantiles, without the distributional assumptions that would be needed for estimation via OLS.

Instead of using OLS regressions, we use quantile regressions to estimate model for different percentiles. We denote the cumulative distribution function (CDF) of ΔZ^j by $F_{\Delta Zj}$ (*), and its inverse CDF by $F^{-1}_{\Delta Zj}$ (q) for the q%

-quantile. It follows immediately that the inverse CDF of $X^j{}_{t+1}$ is

$F^{-1}\, X^{j}_{t+1}(q \mid M_t, X^{j}_{t+1}) = \alpha_q + M_t\, \gamma_q + X^{i}_{t+1}\, \beta_q$

where $\alpha_q = \phi_0 + \phi_3\, F^{-1}\, \Delta Z^j\, (q)$, $\gamma_q = \phi_1 + \phi_4\, F^{-1}\, \Delta Z^j\, (q)$, and $\beta_q = \phi_2$ for quantiles $q \in (0, 100)$. We call F^{-1}_{Xt+1} $(q \mid M^t, X^{i}_{t+1})$ the conditional quantile function. From the definition of VaR, we obtain

$VaR^{j}_{q,t+1}$ = inf {Pr (X_{t+1} | { M_t, X^{i}_{t+1} } ≤ $VaR_{q,t+1}$) ≥ q%} = F^{-1}_{Xt+1} $(q \mid M^t, X^{i}_{t+1})$

$$VaR^{j}_{q,t+1}$$

The conditional quantile function F^{-1}_{Xt+1} $(q \mid M^t, X^{i}_{t+1})$ is the $VaR^{j}_{q,t+1}$ conditional on M^t and X^{i}_{t+1}. By conditioning on = $VaR^{j}_{q,t+1}$, we obtain the $CoVaR^{j|i}_{q,t+1}$ from the quantile function:

$CoVaR^{j|i}_{q,t+1}$ = inf {Pr (X_{t+1} | { M_t, $X^{i}_{t+1} = VaR^{j}_{q,t+1}$} ≤ $VaR^{j}_{q,t+1}$) ≥ q%} = F^{-1}_{Xt+1} $(q \mid M^t, X^{i}_{t+1})$

$$VaR^{j}_{q,t+1} \tag{3.29}$$

We estimate the quantile function as the predicted value of the q% - quantile regression of X^{i}_{t+1} on M_t and X^{j}_{t+1} by solving

$$\min \textstyle\sum_t \cdot \begin{cases} q\% \left|X^{i}_{t+1} - \alpha q - Mt\gamma q - X^{i}_{t+1}\beta q \right| \; if \; \left(X^{i}_{t+1} - q - Mt\gamma q - X^{i}_{t+1}\beta q\right) \geqslant 0 \\ . \\ (1-q\%)\left| X^{i}_{t+1} - \alpha q - Mt\gamma q - X^{i}_{t+1}\beta q \right| \; if \; \left(X^{i}_{t+1} - q - Mt\gamma q - X^{i}_{t+1}\beta q\right) < 0. \\ \alpha q \beta q \gamma q \end{cases}$$

Chapter 4

Contagion, Interdependence and the Impact of Regulation

4.1 Abstract

Using a Markov Switching VAR, we investigate the impact regulation has had on CDS indexes in the US and UK. In so doing, we are able to show the existence of contagion prior to the implementation of regulation and Interdependence after that. We then employed Regime dependent Impulse Response Functions to show the indexes that react most to shocks from the system. We also applied DCC-GARCH to check the robustness of our results that show the Transport, Telecommunications and Electric Power CDS sector indexes exhibit the highest contagion effects in the US, while Banks, Manufacturing and Other Financial Services sector CDS indexes had the most contagion impact in the UK.

4.2 Introduction:

The financial crisis of 2007 that started within the US housing market led to the worst economic collapse since the Great Depression of 1929 (Temin, 2010). The subprime mortgage market in the U.S., where the crisis originated, was less than 4 per cent of the financial system (Settlements, 2009). Yet, this had a substantial impact in the U.S. and around the world. Risk propagation and its transmission across economic sectors and financial markets have many implications for investors, firms, employees and policymakers. Examining the interplay between different sectors is increasingly important as it helps market participants understand how default probabilities evolve and spread during and after crisis periods. This is important because such an understanding provides information about the direction of future defaults, helping market participants' price credit derivatives and hedge credit exposure in the sectoral credit market appropriately. It allows policymakers to formulate their regulation more effectively and holistically.

An ongoing argument is that the excessive use of financial derivatives led to an unprecedented contagion level that affected all economic sectors during the crisis. This chapter's first and principal contribution is analysing the impact regulation has had on credit default swap indexes in reducing contagion. To achieve this, we employ a methodology similar to Guo et al. (2011) and Guidolin and Pedio (2017), i.e. a two-state Markov Switching Vector Autoregressive model (MS-VAR hereafter). The initial state reflects the period of the crisis (high volatility period). The second state accounts for the period regulatory changes were fully phased-in within the derivatives market (announcement started from 2011). The analysis aims to show how the change in the regulatory regime that introduced; central counterparty clearing (henceforth CCP), a Collateral requirement for OTC derivatives, liquidity requirement and Changes to accounts reporting that includes off-balance sheet derivative products is having an impact on reducing the risk of contagion within CDS indexes.

The second contribution of this analysis establishes (using credit default swap spread, henceforth CDS spread) if there was contagion or interdependency within sectors of the economy in the US and the UK during the crisis and if this has changed after introducing regulation. This distinction between interdependence and contagion is of importance to policymakers and investors. That is, in a contagious case, policy intervention could be effective; conversely, in the case of interdependence, a similar action is unlikely to have any significant effect. For example, in the case of interdependence, investors market risk can be reduced by portfolio diversification. However, if contagion occurs, then the degree of dependence between markets increases, and portfolio diversification may not be an effective strategy to follow. Due to the different effects they have on the economic decision process, the identification of interdependence and contagion effects cannot be overemphasized. We follow similar steps used by Celık (2012) to establish this relationship using a two-sample one-sided t-test. It involves testing the change in correlation coefficient between different sample periods that capture the period of volatility (crisis period) and the stable period (after introducing regulation).

Although the concepts of contagion and interdependence are close, there is a subtle and important difference. Longstaff (2010) adopted the definition of contagion use within the literature (such as Bae et al., 2003, Dornbusch et al., 2000, Kaminsky et al., 2003) to be an episode in which there is a significant increase in cross-market linkages after a shock occurs in one market. In comparison, Dornbusch et al. (2000) describe the spillover channels from trade and markets that strengthened linkages or interconnections between sectors and economies as interdependence. Forbes and Rigobon (2002) also define co-movements during stable periods driven by strong connections among markets as “interdependence”. Therefore, the term interdependence here refers to normal co-movements of shocks and provides a baseline to compare the excessive or incremental impact that shocks might have had during crisis periods i.e. Contagion.

The third contribution shows through which channel contagion occurred. That is, which CDS index contributed to the propagation of risk within the economy through the application of Impulse Response Functions (IRF’s). This is similar but different from the work of Longstaff (2010), who analysed the linkages between asset-backed CDO returns, Treasury returns, corporate bond, stock market returns, and changes in the level of the VIX index in three different periods (pre-crisis, the subprime turmoil, and the global crisis periods). His analysis focused on cross-asset contagion within the financial sector and did not consider the impact of regulation as done here.

His analysis is based on simple regressions that assume breaks to be exogenously given while we deal with breaks and instability in the data using Markov regime-switching model. Again, our analysis deals with sectors of the economy as opposed to a single sector.

Another importance of this analysis lies within the regulatory changes introduced after the crisis. Basel III requires all users of OTC products to set aside collateral and report all exposure. There is the introduction of liquidity requirements for using OTC derivatives. The regulation also introduced the CCP's within major national in international regulatory authorities such as; Liineken report in Europe, the Independent Commission on Banking report in the UK and Dodd-Frank Wall-Street Reform and Consumer Protection Act in the US. Their objective is reducing contagion exposure within the sellers and buyers of OTC instruments, especially CDS. This is important as CDS spreads reflect the market's assessment of credit risk (Longstaff, 2010). CDS also serves as an essential indicator of the depth of the crisis and, therefore, suitable for understanding the impact regulation has on contagion (Wang and Moore, 2012). Again, these regulatory measures are aimed at providing safety in terms of increased liquidity, collateral and third party intervention (CCP), all of which further enhance stability and reduce default risk.

Our motivation comes from the understanding that a substantive part of the recent regulation is focused on changing the way financial derivative products are: used, reported, and regulated in order to reduce exposure and contagion. This study aims to better understand the impact regulation is having based on the theme within this thesis. Previous chapters showed the impact of regulation on the probability of financial crisis and systemic risk.

In summary, the literature in this area has focused on either cross-country contagion using homogeneous markets/asset or cross-asset contagion within a single sector. Therefore, we contribute by providing cross-sector contagion using CDS spread within a Regime Switching VAR model to show the impact of regulation on CDS. We establish the existence of contagion or interdependence by comparing the correlation coefficient between the regimes in the MS-VAR model and apply Dynamic Condition Correlation Multivariate Garch (henceforth DCC-GARCH) to check the robustness of our results. Note, while MS-VAR detects regimes from the sample data, for the DCC-GARCH model, we used regulation announcement and compliance dates to differentiate between the two regimes (2007 – 2013 as the period prior to full regulation and 2014 – 2020 as fully regulation compliance period).

Finally, we apply IRF's to establish channels of contagion. Our full sample consist of weekly five year CDS spread Index from January 2007 to January 2020. It covers nine economic sectors that include; 1. Banks, 2. Other financial Services, 3. Manufacturing, 4. Energy, 5. Telecommunications, 6. Consumer Goods, 7. Transportation, 8. Services, and 9. Sovereign Spread. The 2007 crisis provided us a textbook environment to test these relationships. This is because the crisis that started within the subprime market and increased its CDS spread also led to growing CDS spread for all sectors, and the whole economy suffered as a result.

The remaining of this chapter is divided as follows; Section 2 reviews the literature, Section 3 provides explanation of the methodology applied, Section 4 is explanation of the data used for analysis, Section 5 provides the empirical findings of the analysis and we conclude in Section 6.

4.3 Literature Review

When considering the global scope and the devastating effects of the financial crisis, regulatory agencies have placed emphasis on the risks that arise from derivatives. Moreover, the failure of prominent financial giants, such as Lehman Brothers,Bear Stearns, or bailing of American Insurance Group by the government has been widely attributed to their heavy involvement in the CDS market (Borio, 2009). Before the recent crisis, the literature mainly had focused on the dynamics of cross-country contagion applied to homogeneous asset markets (see Forbes and Rigobon, 2002, Markwat et al., 2009). However, since the 2007–2009 US subprime crisis, researchers have shown an increasing interest in cross-asset contagion. This analysis extends the literature by looking into sector contagion/interdependence. We start by briefly looking at literature from theoretical analysis before looking into the empirical analysis.

Kodres and Pritsker (2002) developed a multiple asset rational expectations model of asset prices to explain financial market contagion. Their model allows contagion through several channels with a focus on contagion through cross-market rebalancing. They showed investors transmit idiosyncratic shocks from one market to others by adjusting their portfolios' exposures to shared macroeconomic risks. The pattern and severity of financial contagion depend on markets' sensitivities to shared macroeconomic risk factors and on the amount of information asymmetry in each market. Calvo and Mendoza (2000) used a basic model of international portfolio diversification with incomplete information to show that the globalization of securities markets can reduce incentives for information gathering and hence produce high volatility in capital flows as a result of contagion.

Ballester et al. (2016) highlighted the global financial crisis and subsequent Eurozone crisis has further raised issues associated with interdependence and contagion across firms and industries that disrupt economies as a whole. This, however, does not negate the importance of the network that exists through the interbank market, the payment system, financial markets and so on. Similarly, economies have interconnections through financial and trade linkages. This point to the importance of understanding the exact relationship that exists between sectors (e.g. Coudert and Gex, 2010, Samarakoon, 2011, Guo et al., 2011, Alexakis and Pappas, 2018).

Contrary to the rationale provided for the establishment of CCPs, Arora et al. (2012) pointed out that the OTC derivatives market already have existing arrangements in place to deal with counterparty risk, including the posting of collateral by both counterparties and the use of International Swaps and Derivatives Association (ISDA) master agreements and credit support. If these arrangements are effective solutions to the problem of counterparty risk, central clearing will not contribute to a further reduction in counterparty risk.

Equally, Culp (2015) shows that the imposition of CCPs could lead to many issues such as:(1) Adverse Selection; i.e. the extent that CCPs try and provide clearing and settlement services for non-standardize OTC derivatives as CCP risk managers are likely to be at a serious informational disadvantage to clearing members. (2) Excessive Standardization; counter to the original raison d'etre of the OTC derivatives market – this may pose too many practical problems for CCPs to clear. (3) Margin and Liquidity Risk; i.e. the cost of margin and collateral can be much higher during periods in which derivatives participants have liquidity constrained. This consideration has led to increased interest in understanding the cost of regulation as evidence by the literature.

Furthermore, Heath et al. (2016) illustrate that the concentration in risk can lead to its crystallization if a participant defaults on its obligations to a CCP, given that the CCP must continue to meet its obligations to all of the non-defaulting participants. However, a previous study by Loon and Zhong (2014) tested a similar hypothesis. They used an event-study with the commencement date of central clearing as the event date (day 0) on a sample of 132 reference entities (obligors) for voluntary central clearing between 2009 and 2011. Their results suggest central clearing reduce counterparty risk. On the other hand, Forbes and Rigobon (2002) showed that correlation coefficients are conditional on market volatility. Under certain assumptions, it is possible to adjust for this bias. They concluded that using this adjustment in an empirical study that there was virtually no increase in unconditional correlation coefficients (i.e., no contagion during the 1997 Asian crisis, 1994 Mexican devaluation, and 1987 U.S. market crash). There was, however, a high level of market co-movement in all periods. Suggesting these regulations will not necessarily have an impact on contagion.

These theoretical arguments against the new set of regulations increase the need for rigorous empirical analysis of the impact of regulation. In February 2013, the Over-the-counter Derivatives Coordination Group (ODCG) commissioned the assessment of the macroeconomic implications of over-the-counter (OTC) derivatives regulatory reforms that was undertaken by the Macroeconomic Assessment Group on Derivatives. Their findings show that counterparty exposures related to derivatives traded bilaterally in OTC markets helped propagate and amplify the global financial crisis that erupted in 2008. They concluded that the main benefit of the reforms arises from reducing counterparty exposures through 'netting' as central clearing becomes more widespread and through more comprehensive collateralisation (as set out in recent regulation). Their analysis (using a projection of low, central and high-cost scenarios) show that in the central scenario, regulation lowers the annual probability of a financial crisis propagated by OTC derivatives by 0.26 % points.

Given the vastness of the empirical analysis of contagion and Interdependence, we highlight only the most relevant to this analysis here. In trying to understand if the CDS market was subject to contagion in 2005 General Motors and Ford crisis, Coudert and Gex (2010) applied Exponentially

Weighted Moving Average (EWMA) and DCC-GARCH to check for correlations between CDS premia. They sampled 226 CDSs on major US and European firms. Their results show that correlations significantly increased during the crisis. The crisis also triggered a surge in all CDS premia, making them conclude the presence of industry contagion effect.

Jorion and Zhang (2007) examined the intra-industry information transfer effect of credit events, as captured in the credit default swaps (CDS) and stock markets in the US. They showed that positive correlations across CDS spreads imply that contagion effects dominate, whereas negative correlations indicate competition effects.

Using bank CDS data and its spread as an indicator of credit risk, Ballester et al. (2016) evaluated the contagion among banks in different countries and regions during the crisis via the Generalized Vector Auto-Regressive (GVAR) approach. To distinguish between systematic and idiosyncratic contagion, they applied Principal Component Analysis (PCA) to extract the common factors underlying the correlations among the CDS returns series of individual banks over the sample period. Showing that systematic contagion captures the spillover effects due to changes in global factors that affect all banks, whereas idiosyncratic contagion measures the spillover effects caused by changes in bank fundamentals. They concluded both types of contagion were present from 2007, although the spillover dynamics changed over time.

Longstaff (2010) used a Vector Autoregressive (VAR) framework in testing for contagion from subprime asset-backed collateralized debt obligations (CDOs) and their effects on other markets. His results show that Treasury bond prices increase in response to negative shocks from asset-backed CDO values, consistent with a flight-to-quality pattern. He concluded that contagion appeared to spread from the ABX market at the beginning of the crisis when subprime losses were the primary concern. However, the ABX market no longer functioned as the vector of contagion (and no longer Granger-caused returns) in other markets as the crisis deepened.

Boutabba (2019) analysed the crisis in Thailand's exchange market using the VAR model. He showed evidence of financial contagion between exchange markets, monetary markets, and stock markets and Interdependence with seven other Asian countries. Using weekly Eurozone data from 2007–2014, Guidolin and Pedio (2017) applied a two-state Markov switching model VAR to show contagion effects in a crisis regime. Their findings, mainly explained by a flight-to-quality channel, show that the 2010–2011 European sovereign debt crisis to be a case of cross-country, cross-asset contagion, in which shocks spread from low credit-quality government bonds to corporate bonds and stock markets.

Alexakis and Pappas (2018) applied the multivariate ADCC-GJR-GARCH model within European countries to estimate the dynamic conditional correlations and the Markov-Switching model to identify crisis transition dates for sectorial equity indices (that consist of Financials, Consumer Goods, Telecommunications, Health Care and Industrials sectors) during the 2007 Crisis and European Sovereign Debt Crisis (ESDC). They adjusted the analytical framework to allow for three variants of financial contagion. They first examine each business sector in isolation but across countries. Then analyse specific countries but across sectors and finally looked at financial contagion at cross-country and cross-sector level. Their results confirm contagion for all business sectors under the crisis and ESDC, with Financials and Telecommunications sectors being the most affected, while Industrial and Consumer Goods are the least affected. In addition, all countries experienced financial contagion at varying magnitudes, with those in the Core EU being the most affected in both crises.

Guo et al. (2011) also applied Markov regime-switching VAR to investigate contagion effects among the stock market, real estate market, credit default market, and energy market in the US. They used weekly data of oil price, stock index, CDS index and housing price index from October 2003 through March 2009. Their results showed that the contagion effects among these markets are characterized by nonlinearity with two distinct regimes with stock market activities generating higher volatilities in the CDS market. The contagion effects between stock and energy markets also appear to be larger, while the impacts from the credit default market on the real estate market are not as significant.

Samarakoon (2011) examined the transmission of shocks between the U.S. and foreign markets to differentiate interdependence from contagion during the crisis by constructing VAR shock models for partially overlapping and non-overlapping markets. He concluded that with the existence of important bi-directional yet asymmetric interdependence and contagion in emerging markets. In contrast, Interdependence was driven more by U.S. shocks, while contagion is driven more by emerging market shocks.

Wang and Moore (2012) investigated the correlation of the CDS markets of 38 countries with the US market during the subprime crisis period by applying dynamic conditional correlation from a multivariate GARCH model. Their results provide evidence of correlation during the US subprime-crisis period, particularly highlighting the impact before and after the Lehman collapse and concluded that it would negatively impact risk diversification on international debt.

This discussion provides a synthesis of contagion literature from a theoretical and empirical point of view, with a focus on analysis more relevant to this study. It further clarifies the contribution that this analysis is making to the literature in terms of sector and regulation impact analysis. We now highlight part of the literature that informs the rationale of our methodology choice.

Hou and Nguyen (2018) showed that the MS-VAR model does not restrict the size of the change when a structural break occurs, but it often assumes a small number of in-sample breaks. It also allows for regime recurrence—a feature not assumed in the traditional structural break models. Allowing the regime recurrence does not only tend to improve the estimation accuracy but also helps us to understand more about the interrelationship among the detected regimes. In general, three standard methods can be applied to detect regime-switching. The first method is that we can simply split the sample estimation into different subsamples and test whether there is a structural break.

For example, to study the volatility and the effectiveness of the monetary policy, Blanchard and Gali (2008) and Nakov and Pescatori (2010) simply chose a particular point in time as a breakpoint. With this traditional method, we have to accept the assumption that all model parameters change simultaneously, which is not necessarily the case. More importantly, prior knowledge is often required for determining the break date, which is likely to incur an issue of model misspecification (Boivin and Giannoni, 2006).

Another method often used to study the structural instability in the literature is threshold models. This class of models allows for discrete shifts in the model parameters, like the MS-VAR model, but the researcher has to specify a threshold value or transition variable. Unlike threshold models, the number of regime changes detected by the MS-VAR model is based on a latent Markov process directly estimated from data. In other words, the main advantage of the MS-VAR model over threshold models is that we do not predetermine the threshold value or transition variable before estimation.

The third popular approach in the literature is the time-varying parameter model. This class of non-linear models has been widely used in studying the relationships between macroeconomic variables (e.g. Chan and Eisenstat, 2018, Clark and Ravazzolo, 2015, Cogley and Sargent, 2005, Primiceri, 2005). The time-varying parameter model possesses features that allows it to model gradually changing relationship among the variables of interest. However, the changes in economic structure, like crisis and announcement of regulation did not happen in a gradual manner. In this case, we believe that the MS-VAR model serves as an appropriate tool for modelling structural instability.

Flavin and Sheenan (2015) also pointed out that MS-VAR has certain advantages in that it allows both the mean parameters and variances to switch discretely between two regimes. Regimes are determined endogenously by the data, giving a potentially cleaner delineation between Non-Regulatory Regime and Regulatory Regime. The Regime switch models the heteroskedasticity and overcomes the problem of assuming a constant covariance matrix of innovations.

Finally, Celık (2012) applied the DCC-GARCH model to test the existence of contagion during the Global Financial Crisis. He stated that a major advantage of using this model is the detection of possible changes in conditional correlations over time, which allows the detection of dynamic investor behaviour. Equally, the model is appropriate to investigate possible contagion effects due to herding behaviour in emerging financial markets during crises periods (see Chiang et al., 2007, Corsetti et al., 2005, Syllignakis and Kouretas, 2011). Another advantage of the DCC-GARCH model is that it estimates correlation coefficients of the standardized residuals and so accounts for heteroscedasticity directly (Chiang et al., 2007). Since the volatility is adjusted by the procedure, the time-varying correlation (DCC) does not have any bias from volatility. DCC-GARCH continuously adjusts the correlation for the time-varying volatility. Hence, DCC provides an efficient measure for correlation (Cho and Parhizgari, 2009).

4.4 Methodology

The focus of this analysis is to investigate the impact of regulation on sectoral CDS indexes. We further analyse the existence of contagion or interdependence between CDS indexes of sectors. Finally, we examine the channels through which these occur. To this end, we apply two different models, i.e. the Markov Switching VAR (MS-VAR) and DCC-GARCH, for this analysis. Under the MS-VAR model, we compute impulse response functions (IRFs) to allow us to disentangle channels of contagion. We start by discussing the models individually.

4.4.1 Markov Switching Vector AutoRegression (MS-VAR)

The initial discussion of the MS-VAR model lies in the VAR model. Generally, the VAR approach models every endogenous variable in the system as a function of the lagged values of all of the endogenous variables in the system. Thereafter, the MS-VAR detects regime-switching that necessitate that changes in regimes inherently relates to what occurred in the past regime. This is significantly different from a simple regime model that suggests the break between regimes are not related. This difference is vital to our analysis as we are looking at the impact regulation has had as a result of past volatility.

An essential part of estimating a VAR is dealing with lag length. To choose the appropriate leg length for both our models, we consider the models Akaike information criteria (AIC), the Schwartz information criteria (SIC)and the likelihood ratio test. The standard (single-state) VAR model is defined as follows:

$$y_t = A_0 + \sum_{j=1}^{p} A_j y_{t-j} + \mu_t,\ \mu_t \sim \text{IIDN}\ (0,\ \varepsilon_u) \tag{4.1}$$

Where p indicates the number of lags N x 1.

$y_t = (y_{1,\ t....,}\ y_t)'$ is a N x 1 random vector of endogenous variables.

$A_i = (a_0, \dots\ a_{N,\ 0})$ is a N x 1 vector of intercepts, A_i for i = 1,…,ρ are the N x N vector autoregressive coefficient matrices, and

$u_t = (u_{1,\ t....,}\ u_{N,\ t})'$ is a N-dimensional white noise innovation process, such that $\varepsilon = (u_t)$, $\varepsilon\left(u_t,\ u'_t\right) = \sum_u and \varepsilon\left(u_t, u'_t\right) = 0$ for $s \neq t$ (Enders, 2008).

From above specification, we move to adopt the MS-VAR model that offers a range of benefits as it capture features of the series that a single-state VAR fails to feature, such as; fat tails, heteroskedasticity, skewness, and time–varying correlations (Ang and Timmermann, 2012).

Consider the k-regimes MS-VAR process with heteroskedastic components, compactly MSIAH (k, p) (Markov switching intercept autoregressive heteroskedasticity), defined as:

$$y_t = A_{0,\ St} + \sum_{j=1}^{p} A_{j,\ St} y_{t-j} + \Omega_{St}^{1/2} e_t, e_t\ \text{IIDN}\ (0,\ I_N) \tag{4.2}$$

Where, $S_t = 1,\ 2 \dots k$, k is the number of regimes, p is the number of VAR lags, $A_{0,St}$ is the vector collecting the k regime- -dependent intercepts, and $A_{1,St} \dots A_{j,St}$ are the regime–dependent N x N autoregressive coefficient matrices.

$\Omega_{St}^{1/2}$ is a lower triangular matrix and represents the factors applicable to the regime S_t in a state–dependent Choleski decomposition of the covariance matrix Ω_{St} . In our specification of MS models, we assume that alternative states are possible, that is, k > 1, and that regimes are hidden, meaning that, at all times, investors fail to observe S_t. Moreover, in MS-VAR model, the state S_t is assumed to be generated by a discrete– state, homogeneous, irreducible, and ergodic first–order Markov chain with transition probabilities ξ_t.

$$P_r\!=\!(S_t\!=\!j\ |\{St\}_{j=1}^{t-1},\ \left\{Y\tau\}_{j=1}^{t-1},\right)\!=\!(S_t\!=\!j\ \ |\ S_{t-1}\!=\!i)\ \ P_{i,j}\!=\!\epsilon\ (0,1) \tag{4.3}$$

where $P_{i,j}$ is the generic [i, j] element of the k x k transition matrix P with elements

$$P_{i,j}\!=\!P_r\ \ (S_{t+1}\!=\!j\ \ |\ S_{t=\ i}),\sum_{j=\ 1}^{k} P_i\!=\!1\forall_{i,\ j}\!=\!\epsilon\ \{1\ldots..,k\} \tag{4.4}$$

The elements of the main diagonal of the transition matrix from equation 4.4 estimate the probability of remaining in regime i in two consecutive periods and allow us to capture a persistence in the data that is not linear[1]. MS models are estimated by maximum likelihood (MLE) and estimation is performed through the Expectation–Maximization (henceforth, EM) algorithm proposed by Hamilton (1990). Given the matrix Y_{t-1}, which collects lagged

[1] The equation in (4.2) requires us to estimate many parameters, especially if the number of variables included in the system is large. As an alternative, it is possible to estimate models that require a lower number of parameters than a fully-fledged MSIAH(k,p) framework. For example, in a MSIH(k,0) (Markov switching intercept heteroskedasticity) we have p 1/4 0 and only the intercepts and the covariance matrix of the error terms are regime–dependent. Our specification search selects instead a MSIH(k, p), with p > 0 but the VAR coefficients matrices not linked to the state variable.

values of the variables, and a regime, the density function of $y_t$conditional on the realization of the regime k is Gaussian:

$$p = (y_t | S_t = iY_{t-1}) = \ln(2_{\pi}^{-\frac{1}{2}} \ln|\Omega|_{.}^{-\frac{1}{2}} \exp\left\{(y_t\ y_{k,t})' \Omega_k^{-1} (y_t\ y_{k,t})\right\} \qquad (4.5)$$

If we consider that the information set available at time t-1 includes only the pre–sample values collected in Y_{t-1}, the sample observations, and the states of the Markov chain up to S_{t-1}, then the S_t, Y_τ conditional density of y_t is a mixture of normal distributions:

$$p = (y_t = |S_{t-1} = \sum_{j=1}^{k} \sum_{i=1}^{k} p_{i,j} (\ln(2\pi)_{.}^{-1/2} \ln|\Omega|_{.}^{-1/2} \exp\left\{(y_t\ \bar{y}_{k,t})' \Omega_k^{-1} (y_t\ \bar{y}_{k,t})\right\}). \qquad (4.6)$$

The information about the Markov chain is collected in the vector ξ_t . Because at time t-1 the only information y_t available is the realized time series, we need to estimate, alongside the parameters, also the unobserved regime vector ξ_t . The corresponding estimates are collected in the vector $\xi_{t|\tau}$,

$$\xi_{t|\tau'} = \begin{bmatrix} P_r(S_t = 1 \mid Y\tau \\ \vdots \\ P_r(S_t = k \mid Y\tau \end{bmatrix}$$

To include the probabilities of being in regime k given the information set. If we collect the densities of y_t conditional on and y_{t-1} in the vector η_t, the conditional probability density of y_t given y_{t-1} in equation 4.6 can be written as $p(y_t| yY_{t-1})$ = $\eta_t P\widehat{\xi_{t-1|\tau-1}}$ where $\eta_t \equiv p(y_t| \xi_t = 1Y_{t-1}) \ldots . p(y_t| \xi_t = kY_{t-1})'$. Following the same derivation applied to the single observation y_t , we derive the conditional probability density of the whole sample. The EM algorithm can be used to carry out an iterating process to jointly estimate the parameters and the Markov state probabilities.

Next, we discuss DCC-GARCH model. In doing so, we follow the same assumption applied by Celık (2012), where the test of conditional correlation is used to determine to presence or absence of contagion.

4.4.2 DCC GARCH

In our DCC-GARCH model, we use the same idea in Longstaff (2010), i.e. assuming from our sample that the high volatility period (crisis phase) is exogenous. This coincides with a weekly spread from June 2007 (when Two Bear Stearns funds sold \$4billion of assets to cover redemptions and expected margin calls arising from subprime losses). The new set of regulations were effective from July 2010 (i.e. The US Dodd-Frank Act) and fully phased in by the end of 2013 (which includes; The EU's European Market Infrastructure regulation (EMIR), Markets in Financial Instruments Directive (MiFID) and the Markets in Financial Instruments Regulation (MiFIR)). Therefore, our sample, when testing for the impact of regulation on contagion/Interdependence, starts from 2014.

Let $X_t = [X_t^1, X_t^2]$ be two asset returns with zero means. The returns are assumed to follow a normal bivariate distribution with conditional variance–covariance H_t

$$H_t = \begin{bmatrix} \sigma_{1,t}^2 & \rho_t \\ \rho_t & \sigma_{2,t}^2 \end{bmatrix}$$

The log-likelihood of Xt over the sample t=1 to T is

$$\log L = \frac{1}{2} \sum_{1-t}^{T} 2\log(2\pi) + \log(|H|) + X_t' H_t^{-1 X_t} \quad (4.7)$$

Following Engle and Sheppard (2001) and Engle (2002), the decomposition of the variance–covariance matrix can be written as:

$$H_t = D_t R_t D_t \quad (4.8)$$

Where D_t is the diagonal matrix of the conditional standard deviations and R_t the matrix of the conditional correlations, i.e.

$$D_t = \begin{bmatrix} \sigma_{1,t} & 0 \\ 0 & \sigma_{2,t} \end{bmatrix}, R_t = \begin{bmatrix} 1 & \rho_t \\ \rho_t & 1 \end{bmatrix}$$

By replacing H_t with this decomposition in the log-likelihood, the equation can be written as:

$$\log L = \frac{1}{2} \sum_{1-t}^{T} 2\log(2\pi) + \log(|D_t|)\ \log(|R_t|) + \varepsilon_t^{'} D_t^{-1} R_t^{-1} D_t^{-1} \varepsilon_t \tag{4.9}$$

The maximisation of the log-likelihood is done in two steps. The first one consists in maximising the likelihood on matrix D_t. To do so, volatilities are estimated through univariate GARCH:

$$D_t = \overline{D}\ (1 - A - B) + A_{xt-1} x^{'}_{t-1} + BD_{t-1} \tag{4.10}$$

where A and B are diagonal matrixes. In a second step, the returns X_t are divided by their estimated standard deviations. The reduced returns $\varepsilon_t = D_t^{-1} x_t$ are used to estimate the dynamic correlations:

$$Q_t = \overline{Q}\ (1 - \propto - \beta) + \alpha \varepsilon_{t-1} 1 \varepsilon^{'}_{t-1} + \beta Q_{t-1} \tag{4.11}$$

$$\overline{Q} = \frac{1}{n} \sum_{t-1}^{T} \varepsilon_t \varepsilon_t^{'} \tag{4.12}$$

where α and β are matrices with diagonal elements equal to a and b, respectively. To obtain the correlation matrix, the elements of Q_t are normalized by dividing by the standard deviations:

$$R_t = \mathrm{diag}(Q_t)^{-\frac{1}{2}} \ \ Q_t \mathrm{diag}(Q_t)^{-\frac{1}{2}} \tag{4.13}$$

$$\overline{Q_t} = \frac{q_{12,t}}{\sqrt{q11,t} \ \ \sqrt{q22,t}} \tag{4.14}$$

Following the analysis of Celık (2012), we further use t-statistics to test consistency of dynamic correlation coefficients between the two samples of all CDS indexes in both countries in order to establish the existence of contagion/interdependence effects. We use a one-sided test for mean differences between samples that allows us to conclude if the means of conditional correlations are different between crisis period (before regulation) and tranquil period (regulation period). If conditional correlations were higher during crisis periods, this would constitute a contagion effect. We define null and alternative hypotheses as:

$$H_o: \mu_\rho^{crisis} = \mu_\rho^{regulation}, \qquad H_1: \mu_\rho^{crisis} > \mu_\rho^{regulation} \tag{4.15}$$

Where μ_ρ^{crisis} and $\mu_\rho^{regulation}$ are the conditional correlation coefficient means of population in the crisis and regulatory periods. If the sample sizes are n^{crisis} and $n^{regulation}$, the population variances σ^2_{crisis} and $\sigma^2_{regulation}$ are different and unknown. Then the means of dynamic correlation coefficients estimated by DCC are $\widetilde{\rho}_{ij}^{crisis}$ and $\widetilde{\rho}_{ij}^{regulation}$ and the variance are s^2_{crisis} and

$s^2_{regulation}$, the t-statistics is then calculated as:

$$t = \frac{\left(\widetilde{\rho}_{ij}^{crisis} - \widetilde{\rho}_{ij}^{regulation}\right) - (\mu_{\rho}^{crisis} - \mu_{\rho}^{regulation})}{\sqrt{\frac{s^2_{crisis}}{n^{crisis}} + \frac{s^2_{regulation}}{n^{regulation}}}} \tag{4.16}$$

Where: $s^2_{crisis} = \frac{1}{n^{crisis}-1} \sum_{t=1}^{n} crisis(\rho_{ij}^{crisis} - \widetilde{\rho}_{ij}^{crisis})$, and $s^2_{regulation} = \frac{1}{n^{regulation}-1} \sum_{t=1}^{n} regulation(\rho_{ij}^{regulation} - \widetilde{\rho}_{ij}^{regulation})$, then the degrees of freedom

$$\vartheta = \frac{\left(\frac{s^2_{crisis}}{n^{crisis}} + \frac{s^2_{regulation}}{n^{regulation}}\right)^2}{\frac{\left(\frac{s^2_{crisis}}{n^{crisis}}\right)^2}{n^{crisis}-1} + \frac{\left(\frac{s^2_{regulation}}{n^{regulation}}\right)^2}{n^{regulation}-1}} \tag{4.17}$$

Therefore, If t-statistics is significantly greater than the critical value, H_0 is rejected supporting the existence of contagion effect. Given the discussions above on MS-VAR and DCC-Garch, we can finally we look at IRF's.

4.4.3 Impulse Response Functions (IRFs)

According to the general definition, an IRF represents the difference between the conditional expectation of y_{t+h} at time t in case y_t has been subject to a shock and the conditional expectation of y_{t+h} at time t in case y_t has not been subject to any shock. In practice, we can define the h–step ahead IRF as follows

$$IR_{\Delta u}(h) = E[Y_{t+h} | \, y_t \, (\omega^{'})] - E[Y_{t+h} | \, y_t \, (\omega)] \tag{4.18}$$

Where, the sample path $y_t \, (\omega^{'})$ differs from the sample path $y_t \, (\omega)$ because the initial value of y_t has been subject to a shock. This general definition can be extended and adapted to a MS framework. In this case, we obtain the following representation:

$$IR_{\Delta u}(h) = E\left[Y_{t+h} | \xi_t, \, u_t + \Delta u_t, Y_{t-1}\right] - E\left[Y_{t+h} | \xi_t, \, u_t + \Delta u_t, Y_{t-1}\right] \tag{4.19}$$

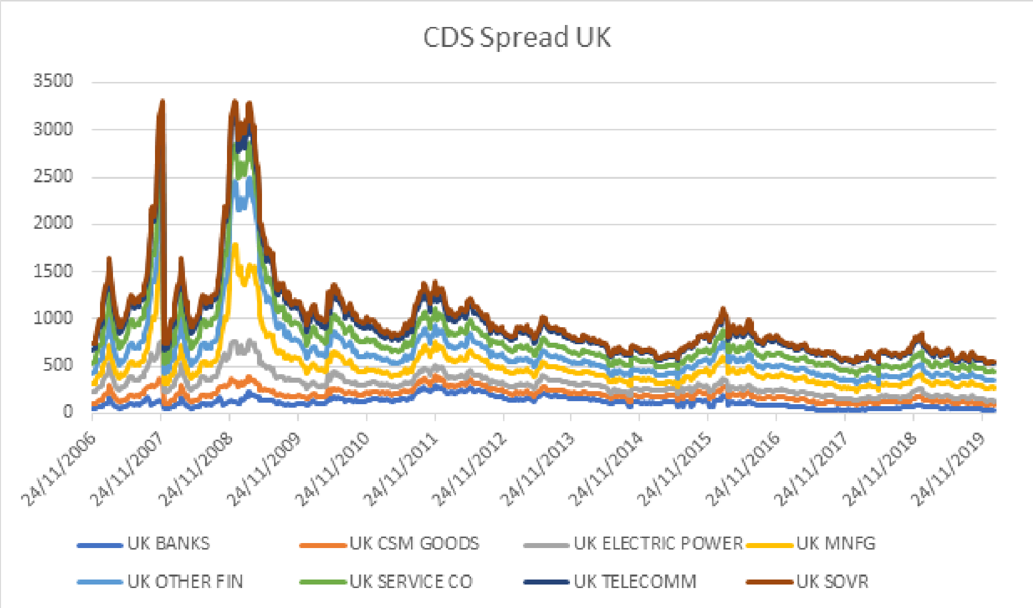
The h-step ahead IRF thus depends on the state prevailing at time t, when the shock occurs. However, when computing IRFs in a MS framework we need to deal with the additional issue that regimes are latent and therefore the prevailing state at time t is unobservable. For this reason, we compute regime–dependent IRFs under the assumption that we know the regime prevailing at the time the shock occurs. Both reduced- form VAR and MS-VAR models are subject to identification problems. Therefore, we apply a Choleski decomposition to the regime–dependent covariance matrices (as we do in the case of single state model). A Choleski triangular factorization allows solving the identification problem without imposing structure.

Because it forces asymmetries in the model, the ordering of the variables becomes crucial. To control for this drawback, we apply different orderings to the series and verify that the results are stable. In addition, to account for the uncertainty of the estimated values, for each IRF we also construct the appropriate confidence intervals through Monte Carlo simulation techniques.

4.5 Data

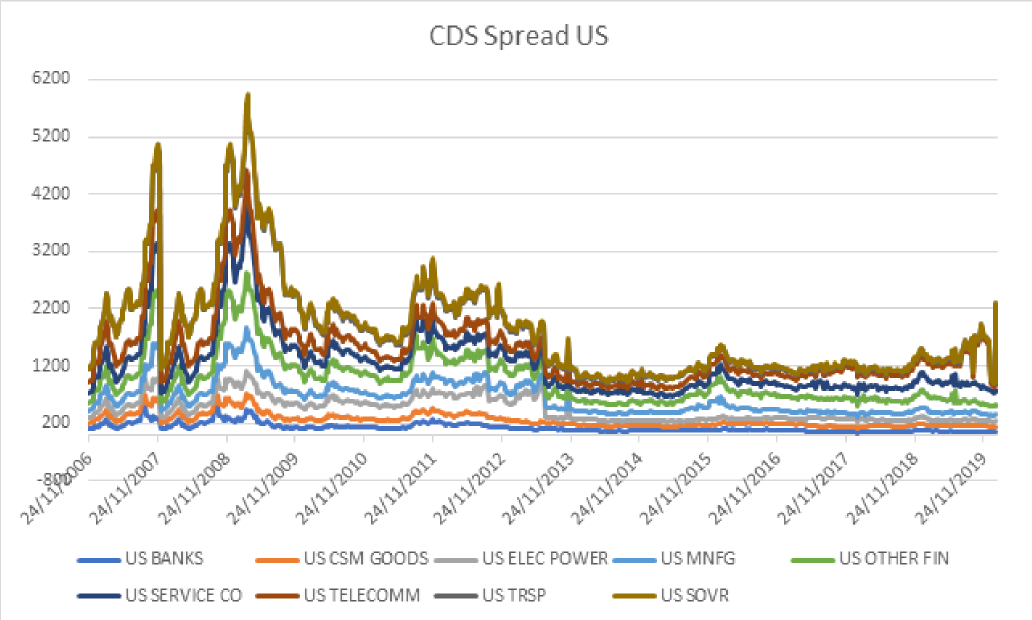
We use only 5-year CDS spreads because these contracts are the most liquid and constitute over 85% of the entire CDS market. To maintain uniformity in contracts, we only keep CDS quotations for senior unsecured debt with a modified restructuring (MR) clause and denominated in US dollars. Our choice of sector follows the literature such as Guo et al. (2011), However, given our understanding of how regulation is focused towards impacting the whole CDS market directly, we choose the most relevant sectors in the economy that show high use of CDS according to the data and literature. These include 1.Banks, 2.Other financial Services, 3.Manufacturing, 4.Energy, 5.Telecommunications, 6. Consumer Goods, 7. Transportation, 8. Services, and 9. Sovereign Spread.

Figure 4.1: UK CDS spread



Note: Weekly UK sectors CDS spread series over the sample period. Source: Author.

Figure 4.2: US CDS spread



Note: Weekly US sectors CDS spread series over the sample period.Source: Author.

A cursory look at the Graphs above may suggest that our weekly sector CDS series are non-stationary. We, therefore, transform all series by taking the first difference. Please note that while both series show spikes around the same period, a careful look will suggest that the spike in the UK is a little later than in the US (although difficult to show using weekly data for the time period). In addition, Graph 1 has Y-axis that reaches 6500, while Graph 2 peaks at 3500, showing that volatility in the US was much more when compared to the UK. The volatility also lasted much longer in the US than UK from comparing both graphs. Below is the CDS indexes descriptive data table.

Table 4.1: Weekly CDS Descriptive Statistics

CDS INDEX	mean	max	min	sd	skewness	kurtosis	ADF
US BANKS	117.7	511.96	21.77	71.85	1.93	7.73	-18.17
US CSM GOODS	127.74	343.91	76.81	43.55	1.57	6.1	-15.99
US ELEC POWER	192.68	663.21	78.22	121.26	1.09	3.59	-22.06
US MNFG	192.08	765.95	68.22	101.63	2.95	13.03	-20.98
US OTHER FIN	309.69	984.76	145.1	146.3	2.02	7.72	-14.59
US SERVICE CO	267.55	1186.4	132.77	140.95	3.28	16.02	-16.79
US TELECOMM	245.07	1454.43	107.09	138.16	3.09	17.99	-15.49
US TRSP	307.48	1363.3	53.74	193.58	1.72	5.77	-13.36
US SOVR	27.45	95	6.10	14.70	1.23	4.97	-19.35
UK BANKS	120.77	305.47	33.96	57.65	0.65	3.02	-18.61
UK CSM GOODS	79.08	227.58	49.04	25.19	3.11	14.71	-15.62
UKELEC POWER	103.88	419.51	41.55	68.77	2.52	9.69	-15.52
UK MNFG	180.79	1029.17	66.8	138.02	4.02	19.98	-11.40
UK OTHER FIN	155.74	932.16	78.75	129.31	3.76	18.29	-11.33
UK SERVICE CO	140.12	402.59	74.41	58.72	2.36	8.91	-16.72
UK TELECOMM	149.58	409.88	79.94	52.51	1.74	7.10	-16.49
UK SOVR	40.15	165	10.76	26.68	1.55	5.86	-18.84

Notes:Table 4.1 contains descriptive statistics of weekly CDS spread for the indexes chosen within the US and UK economies from January 2007 to January 2020 (for US/UK abbreviations are: Consumer goods (csm goods), Electric power (elec power), Manufacturing (manufacturing), Other financial services (other fin), Service companies (Service co), Telecommunications (Telecomm), Transport (Trsp), Sovereign (Sovr). Full names of CDS index in index). For the ADF test, the critical values at 1%, 5% and 10% significant levels are -3.47, -2.88 and -2.58, respectively.

Prior to the identification of possible long-term relations of the variables specified in the MS-VAR system, it is necessary to verify that all variables are stationary since lack thereof can make any empirical results deceptive. Table 4.1 presents the stationarity results for all the variables, based upon the Augmented Dickey-Fuller unit root test, which corrects any possible presence of autocorrelation in the standard ADF test in a non-parametric way. We find that all series are I(0).

The table consists of all indexes used for the analysis in the UK and US. The Sovereign spreads for both countries has the smallest mean values, supporting the understanding that it pays out only in circumstances of debt default, whereas corporate debts payout in situations of bankruptcy, restructuring or any other defined credit event. This suggests the stability of sovereign CDS as compared to CDS indexes within sectors of the economy. The mean of US other financial index is the highest, supporting the evidence that the crisis was more prominent this sector as it covers all financial services other than banks, with the literature showing that the failure of firms like Lehman and Bear Stearns propelled the crisis (they were also heavily invested in the CDS market).
The table also shows that the index with the highest minimum value is also the US other financial index. Looking at the kurtosis and the skewness of all the series, it shows a generally positive skewness of the spread and peaked Kurtosis that confirms fat tails. This is evidence for abnormal events or large shocks. The highest mean values for the UK CDS indexes are the manufacturing and Banking sector. They also exhibit comparatively higher standard deviations, suggesting these series suffer more fluctuations through the sample period.

While it is possible to sample the data into different periods to gain some basic understanding, we use the whole sample period instead (as our analysis uses MS-VAR to detect different regimes in the data). This also allows us to appreciate the movement of spread over the sample period. The CDS spread graphs (for US and UK) above capture this movement, showing some level of a spike in 2007 when the crisis is said to have started and a significant spike that captures the height of the crisis in 2008. It also shows some level of stability that is consistent with the regulatory period.

We use weekly data for this analysis as it allows us to capture the fluctuations within these sectors without incorporating the noise that is often found in daily data. On the other hand, monthly data produces too few data points for VAR analysis and therefore not used in our analysis. The CDS data is retrieved from DataStream, covering the period from January 2007 through January 2020. This constitutes the longest recent sample in any study within similar literature. Also note, similar to the way a stock index is created as a portfolio of individual stocks, a CDS index is essentially a portfolio of single-name credit default swaps.

From our methodology discussion, we indicated one of the important issues in constructing a VAR model is a proper choice of the lag length. This is sometimes a matter of judgement based on the theory and nature of the data used for analysis. However, there are statistical procedures that determine the appropriate lag length, such as the Akaike information criteria (AIC), the Schwartz information criteria (SIC) and the likelihood ratio test (Barrell et al.). Equally, a range of standard information criteria (IC) that trade-off in sample fit with model parsimony provides heterogeneous indications about what should be the appropriate number of VAR lags. The table shows the criteria use here.

Table 4.2: Selection Criteria (US)

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-27225.8				3.409	87.154	87.182	87.255*
1	-26941.7	568.1	100	0	1.909	86.565	86.869*	87.346
2	-26841.1	201.34	100	0	1.909	86.563	87.142	88.054
3	-26766.5	149.17	100	0.00	2.005	86.644	87.501	88.845
4	-26618.3	296.43	100	0	1.251*	86.495*	87.621	89.401
5	-26549.2	138.15	100	0.07	1.909	86.589	87.996	90.210
6	-26453.6	191.15	100	0	1.909	86.604	88.286	90.934
7	-26374.9	157.5	100	0	2.109	86.671	88.631	91.718
8	-26307.9	133.5*	100	0.01	2.302	86.777	89.012	92.523

Notes: The table shows four information criteria as well as a sequence of likelihood ratio (LR) tests for the US. These are; SBIC(The Bayesian information criterion), HQIC (Hannan–Quinn information criterion), Akaike information criteria (AIC) and Final prediction error (FPE). Strictly speaking, the FPE is not an information criterion, though we include it in this discussion because, as with an information criterion, we select the lag length corresponding to the lowest value; and, naturally, we want to minimize the prediction error. Star shows the most efficient criteria at the relevant lag. lag.

Table 4.3: Selection Criteria (UK)

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1745	2.601	55.879	55.901	55.936			
1	-1723	462.280	64	0	1.505	55.345	55.543	55.856*
2	-1709	255.700	64	0	1.208	55.141	55.512	56.106
3	-1699	196.361	64	0	1.108	55.031	55.583	56.451
4	-1687	253.840	64	0	9.001	54.829	55.558	56.704
5	-1671	319.572	64	0	6.607	54.523	55.428	56.852
6	-1657	267.271	64	0	5.309	54.304	55.382	57.084
7	-1645	249.821	64	0	4.409	54.105	55.363	57.343
8	-1631	271.941*	64	0	3.519*	53.875*	55.309*	57.567

Notes:The table shows four information criteria as well as a sequence of likelihood ratio (LR) tests for the UK. These are; SBIC(The Bayesian information criterion), HQIC (Hannan–Quinn information criterion), Akaike information criteria (AIC) and Final prediction error (FPE). Strictly speaking, the FPE is not an information criterion, though we include it in this discussion because, as with an information criterion, we select the lag length corresponding to the lowest value; and, naturally, we want to minimize the prediction error. Star shows the most efficient criteria at the relevant lag.

From above, we can therefore conclude that the appropriate lag length for the US is lag 4. This is based on the results in Table 4.2 that shows at lag 4 we have the minimum AIC and FPE tests result. Although, the HQIC and SBIC support no lag and lag one, we think that just one lag may not be enough to investigate the causal relationship over long periods. Therefore, we used the lag length suggested by the AIC test (four lags for the period before the crisis and six lags for the period after the crisis). The UK series lag length base on selection criteria test is lag 8. This is because all the tests synonymously (other than the SBIC) show that it is the appropriate lag length.

4.6 Key Empirical Results

We start by discussing results from our main model, MS-VAR and then the Garch model before interpreting our IRF results. Remember that the MS-VAR model does not require any assumptions on the timing of the regime episodes; It infers the probability of being in a specific state as well as the probability of switching from one state to the other (as explained earlier in the model). The transition between the different regimes is modelled as a hidden Markov chain. The transition matrix allows for a differentiated analysis of the dynamics of entering and exiting regimes, allowing for a non-symmetric analysis of all turning points.

4.6.1 MS-VAR

We start by discussing regime probabilities and duration before looking at index mean values. Table 4.2 shows that our US data exhibit two different regimes. This is in line with the data we collected that covers the crisis period with high volatility i.e. 2007-2013 and stable period, i.e. period where regulation was put in place (2014 – 2020). Our initial regime $p_{1,1}$ shows a high regime 1 probability of 0.89%, reflecting the nature of volatility witnessed during the crisis. $p_{1,2}$ represent the transition probability of regime 1 moving into regime 2. This probability of 39% seem low as the US government did swiftly acted to restore market confidence even before regulation was put in place.

The empirical evidence for this is that on December-12-2007, The US Treasury launch the temporary Term Auction Facility (TAF) to address pressures in short-term funding markets. On February-13-2008 President Bush signed the Economic Stimulus Act of 2008 into law. By March 2008, Federal Reserve announce creation of Term Securities Lending Facility (TSLF). On September-16-2008 Federal Reserve authorized lending up to $85 billion to AIG. In October 2008, Congress passes Emergency Economic Stabilization Act, providing $700 billion to the Troubled Asset Relief Program (TARP). Furthermore, in November 2008 Federal Reserve Board announces creation of Term Asset-Backed Securities Lending Facility (TALF) and in December 2008 U.S. Treasury authorizes special loans for General Motors and Chrysler (Longstaff, 2010). Perhaps with these interventions we expected the Regime $p_{1,2}$ to be much higher. This shows how endemic the crisis was and the impact it had on CDS indexes, supporting the implementation of a wide and unprecedented set of regulations.

The US Regime 2 has a probability of 0.60% as shown by $p_{1,2}$, this is relatively lower than regime 1. The transition probability of regime 2 going back to regime 1 is also comparatively higher at about 0.40%. Both figures highlights the impact the crisis has had on CDS market. Where before the crisis, the CDS notional values was around $62 trillion, however during the crisis it dropped to about $10 trillion and in 2019 to about $4 trillion. The result also points to the probability of indexes being more likely to experience volatility, consistent with the nature of CDS markets. Regime 1 is expected to last for 47 weeks, while Regime 2 expected duration is 157 weeks. This is reasonable considering the swift reaction by the authorities and the impact of regulation on CDS indexes.

Table 4.3 shows CDS index regimes in the UK. These results are similar to US results with respect to regime probabilities and transitions. Like the US, the UK also had in place measures that supported the economy before the implementation of the regulation. However, the table shows that in the UK, Regime 1 had a shorter duration (36 weeks), while Regime 2 has a longer duration (177 weeks) when compared to the US. This result supports empirical evidence that shows the UK experienced a shorter crisis period, fewer failed institutions and faster response by authorities as compared to the US. It also suggests that regulation in the UK seem to have

Table 4.4: US Regimes

Index	TELCOMM	BANKS	CSMGD	ELEC.P	MNFRG	OTHER.F.I	SERV.CO	SOVR	TRNSPT
μ_1 regime 1	-0.869	-1.901	-0.524	-2.455	-0.839	-2.005	-1.054	-0.257	-5.454
μ_2 regime 2	11.718	11.618	3.025	7.841	3.842	7.636	10.698	1.899	15.536
$p_{1,1}$									0.887
$p_{1,2}$									0.395
$p_{2,1}$									0.112
$p_{2,2}$									0.604
Expected duration of regime 1									47.006
Expected duration of regime 2									157.750

Notes:Table shows US index regime mean values and the transition probabilities and expected durations for each regime. $_1$ and $_2$ represent the two regimes. $p_1, 1$ shows the probability of regime 1 not switching, while $p_1, 2$ shows the probability of it moving into regime 2. In same manner, $p_2, 2$ shows the probability of regime 2 not switching, while $p_2, 1$ shows the probability of it moving into regime 1.

Table 4.5: UK Regimes

Index	TELCOMM	BANKS	CSMGD	ELEC.P	MNFRG	OTHER.F.I	SERV.CO	SOVR
μ_1 regime 1	-1.103	-	-0.454	-0.419	-1.047	-0.453	-0.518	-
		0.645						0.315
μ_2 regime 2	2.802	3.063	1.375	0.484	1.794	0.892	1.033	0.892
$p_{1,1}$								0.874
$p_{1,2}$								0.373
$p_{2,1}$								0.125
$p_{2,2}$								0.627
Expected duration of regime 1								36.006
Expected duration of regime 2								177.751

Notes:Table shows UK index regime mean values and the transition probabilities and expected durations for each regime. $_1$ and $_2$ represent the two regimes. $p_1, 1$ shows the probability of regime 1 not switching, while $p_1, 2$ shows the probability of it moving into regime 2. In same manner, $p_2, 2$ shows the probability of regime 2 not switching, while $p_2, 1$ shows the probability of it moving into regime 1.

more impact on CDS indexes as Regime 2 is longer and the probability of transitional back to Regime 1 (a period that is more volatile) is lower than the US.

We now discuss the mean CDS index through both regimes in table 4.2 & 4.3 above, where μ_1 regime 1 are the mean values in Regime 1, and μ_2 regime 2 the mean values in Regime 2. Both tables show the expected impact that regulation has had on these indexes. Meaning, all CDS indexes in both countries have moved from being negative in Regime 1 to positive in Regime 2. This is a strong evidence of the impact regulation has had on these indexes.

Table 4.2 provide some interesting results on US CDS indexes. Starting with SOVR index. This is consistent with what we expected to have occurred. It shows the least fluctuation between the two regimes, while the CDS index in other economic sectors declined in regime 1, Sovereign CDS Index shows only a comparatively slight decline at -0.257. It has the least increase in regime 2, therefore comparatively more stable. The intuition here is that sovereign CDS backed by government is associated with more investor confidence and perceived to be less risky than other sectors. The unexpected result is with Transport (TRNSP) and Electric Power (Elec. P) sector CDS indexes. They witnessed the most fluctuations between the 2 Regimes, with Regime mean index drop of -5.454 and -2.455 and growth of 15.536% and 7.841% respectively.

Our explanation for these is that the slowdown in economic activities has affected companies in these sectors relatively hard. Whereas, Banking (Banks), Other Financial Institutions (Other F.I) and Service Companies (Serv. Co) sector indexes display somewhat similar regime changes, although given the crisis seemingly had more effect on institutions covered by these indexes, we expected them to have the highest drop in Regime 1. The growth we see in them can be explained by the fact that these sectors received a lot government support and regulation aimed at restoring confidence was focused on the activities of these sectors.

Table 4.3 shows the mean changes between Regimes in UK indexes. It has a slightly different result from the US, as the Electric Power not Sovereign CDS index shows the least fluctuation. Banking and Service Companies CDS indexes experience the highest change between the means of the two Regimes. This is in line with empirical evidence as UK government intervention meant ownership of about 70% of most of the major Banks.

Having discussed Regimes, transition probabilities and index Regime mean, the next part of the analysis discusses contagion and interdependence between CDS indexes over the two regimes. To discuss these we use a combination of tables from 4.6 to 4.9 below. Table 4.6 & 4.5 provides us the results of our Regime 1 MS-VAR models and tables 4.6 & 4.7 are Regime 2 results. Tables 4.8 & 4.9 show the results from t-statistics of regimes correlations coefficients. Furthermore Table 4.10 & 4.11 are results from index correlation coefficient t-statistics tests. Finally, tables 4.12 & 4.13

are robustness results from DCC-Garch model.

Regime 1 covers the period of volatility (financial crisis) and prior to regulation. Therefore, the existence of statistically significant index coefficient, high correlation, along with t-test result as compared to Regime 2 shows the existence of contagion. While Regime 2 covers the period that regulation has been fully phased-in and complied with, therefore more stable. The presence of statistically significant index coefficient, t-test result and low correlation as compared to Regime 1 shows interdependence. Please note we only report few correlation results[2] from Table 4.10 & 4.11 below that highlights results different from what we expected in our analysis. This is because we have 9 CDS sector index in the US and 8 in the UK that resulted in producing index correlation combinations amounting to 46 in the US and 28 in the UK.

[2] I have presented the whole result in the index section.

Table 4.6: MS-VAR US Regime 1

	Variable	Coeff	Std. Error	T- Stat	Signif
1	TELECOMMS	-0.666	0.578	-1.152	0.249
2	BANKS	-1.272	0.464	-2.735	0.006
3	CSMGOODS	-0.521	0.216	-2.415	0.016
4	ELECT.POWER	-0.661	1.187	-0.556	0.577
5	MANUFACTURING	-0.818	0.344	-2.374	0.017
6	OTHER FIN.INST	-2.071	1.005	-2.058	0.039
7	SERVICE COMP	-1.067	0.511	-2.085	0.036
8	SOVEREIGN	-0.119	0.086	-1.385	0.165
9	TRANSPORT	-0.046	1.582	-2.557	0.010

Notes:This table shows period of volatility (i.e. pre-regulation period) MS-VAR index results in the US. The indexes are: Consumer goods (csm goods), Electric power (elec power), Manufacturing (manufacturing), Other financial services (other fin), Service companies (Service co), Telecommunications (Telecomm), Transport (Trsp), Sovereign (Sovr).

Table 4.7: MS-VAR UK Regime 1

	Variable	Coeff	Std. Error	T- Stat	Signif
1	TELECOMMS	-0.964	0.314	-3.071	0.002
2	BANKS	-0.611	0.285	-2.144	0.032
3	CSMGOODS	-0.333	0.128	-2.586	0.009
4	ELECT.POWER	-0.443	0.187	-2.359	0.018
5	MANUFACTURING	-0.914	0.488	-1.873	0.060
6	OTHER FIN.INST	-0.244	0.309	-0.790	0.029
7	SERVICE COMP	-0.465	0.193	-2.408	0.015
8	SOVEREIGN	-0.358	0.147	-2.431	0.015

Notes:This table show tranquil period (i.e. regulation period) MS-VAR index results in the UK. The indexes are: Consumer goods (csm goods), Electric power (elec power), Manufacturing (manufacturing), Other financial services (other fin), Service companies (Service co), Telecommunications (Telecomm), Transport (Trsp), Sovereign (Sovr).

Tables 4.6 & 4.7 show the results from Regime 1 US and UK MS-VAR models. All the coefficients reflect the negative impact of crisis. Looking at US indexes, The Telecomms, Electric Power and Sovereign indexes coefficients are not statistically significant at the 5% level. Therefore, we cannot draw the conclusion that these indexes suffered from the impact of contagion within Regime 1. This is consistent with earlier results from regime switching mean values in Regime 1 that showed Telecomms and Sovereign indexes suffered the least fluctuations throughout the period. The model confirms what we suspected, i.e. Other Financial Institutions and Banks indexes experienced the most negative impact of contagion within the model. This is consistent with the result in Guo et al. (2011) and supports the earlier discussion that these sectors used CDS products more within the economy.

Contrary to Table 4.6, the UK Regime 1 MS-VAR model in Table 4.7 above that shows all index coefficients to be statistically significant, showing the existence of contagion in all indexes. Here, the Telecomms and Manufacturing indexes coefficients show higher negative impact compared to the remaining indexes. This is despite the empirical evidence with Northern Rock failing and HBOS taken over by Lloyds Bank, as a result of excessive use of CDS (Ballester et al., 2016). Perhaps an explanation for this was the move by UK government to directly take over most of UK Banks (unlike in the US) and therefore providing more stability to this sector, however not avoiding overall contagion within all indexes. This becomes even clearer when we look at the results from Regime 2 that shows most of the

UK indexes still exhibit high correlation to UK sovereign CDS index.

Table 4.8 provides US Regime 2 MS-VAR model. It shows that all indexes in the system have been positively impacted by the introduction of regulation. There is also a change in correlation between most of the indexes that allows us to draw the conclusion that Regime 2 reflects a change in relationship from contagion to interdependence, with the exception of Telecomms index that is not statistically significant. The index of Banks, Other Financial Institutions and Service Companies show the most change, where their index coefficients have moved from - 1.271696, -2.070563, -1.06744 in Regime 1 to 7.55356, 16.6562 and 8.08568 respectively. The result remains consistent with respect to the Sovereign index that shows least change.

Table 4.8: MS-VAR US Regime 2

	Variable	Coeff	Std. Error	T-Stat	Signif
1	TELECOMMS	1.612	3.378	0.477	0.631
2	BANKS	7.553	1.121	6.733	0.000
3	CSMGOODS	3.808	0.332	11.438	0.010
4	ELECT.POWER	2.148	2.090	10.592	0.010
5	MANUFACTURING	7.075	0.843	8.390	0.001
6	OTHER FIN.INST	16.656	1.884	8.839	0.003
7	SERVICE COMP	8.085	1.421	5.688	0.011
8	SOVEREIGN	0.983	0.133	7.369	0.000
9	TRANSPORT	8.347	2.282	3.656	0.000

Notes:This table show tranquil period (i.e. regulation period) MS-VAR index results in the US.The indexes are: Consumer goods (csm goods), Electric power (elec power), Manufacturing (manufacturing), Other financial services (other fin), Service companies (Service co), Telecommunications (Telecomm), Transport (Trsp), Sovereign (Sovr).

The UK Regime 2 MS-VAR results in Table 4.9 below, shows generally the impact of regulation is positive on all the indexes, with the exception of Electric Power index coefficient that is not statistically significant. It shows that index of banks, Telecomms and Manufacturing experienced the most positive change from the previous Regime. We therefore conclude after comparing the correlation results that these indexes show a change in relationship from contagion to interdependence after the introduction of regulation. However, the relationship between the Sovereign CDS index and those of Banks, Consumer goods, Electric power, Other financial institution and Telecomms have increased from Regime 1 to Regime 2. Suggesting that these indexes have greater relationship with Sovereign CDS index than before the implementation of regulation. Leading us to suggest that while the intervention by UK government over failing institutions supported in overcoming the effects of contagion and therefore bringing stability to the system, it has also brought about closer relationship between economic sector CDS indexes and that of the government. Implying that the current risk associated with sector indexes is associated with that of government CDS index. Hence, these close relationship between indexes that government CDS index.

Table 4.9: MS-VAR UK Regime 2

	Variable	*Coeff*	*Std. Error*	*T-Stat*	*Signif*
1	TELECOMMS	1.668	0.491	3.396	0.000
2	BANKS	1.817	0.663	2.740	0.006
3	CSMGOODS	0.755	0.225	3.350	0.000
4	ELECT.POWER	0.043	0.416	0.103	0.917
5	MANUFACTURING	1.267	0.697	1.816	0.069
6	OTHER FIN.INST	0.653	0.580	1.125	0.060
7	SERVICE COMP	0.656	0.344	1.901	0.056
8	SOVEREIGN	0.796	0.225	3.534	0.000

Notes:This table show tranquil period (i.e. regulation period) MS-VAR index results in the UK. The indexes are: Consumer goods (csm goods), Electric power (elec power), Manufacturing (manufacturing), Other financial services (other fin), Service companies (Service co), Telecommunications (Telecomm), Transport (Trsp), Sovereign (Sovr).

To support these conclusions, we applied the t-stat. test between regime mean correlation coefficients. That is, we tested the null hypothesis that Regime 1 minus regime 2 is equal to zero against the alternative hypothesis that Regime 1 is statistically higher than Regime 2 (see Celık (2012) & Bratis et al. (2018)). The results are captured below in Tables 4.10 & 4.11

for both countries.

Table 4.10: US Regimes test result

Variable	*Obs*	*Mean*	*Std.Err*	*Std.Dev*	*95%Conf.Int*
Crisis Corr.Coeff's	36	0.411	0.035	0.214	0.338 - 0.484
Reg. Corr.Coeff's	36	0.085	0.018	0.111	0.047 - 0.122
Combined	72	0.248	0.027	0.236	0.192 - 0.303
Diff		0.326	0.040	0.364	0.246 - 0.406

diff = mean (Crisis Corr.Coeff's) - mean (Reg. Corr.Coeff's) t = 8.109
$\mathbf{H_o}$: diff = 0 degrees of freedom = 70
$\mathbf{H_1}$: diff < 0 $\mathbf{H_1}$: diff = 0 $\mathbf{H_1}$: diff > 0
Pr(T < t)=1.000 Pr(T > t)=0.000 Pr(T > t)=0.0000

Notes: This table shows the t-stat test result for the US CDS correlation coefficient regimes.

Table 4.11: UK Regimes test result

Variable	*Obs*	*Mean*	*Std.Err*	*Std.Dev*	*95%Conf.Int*
Crisis Corr. Coeff's	28	0.514	0.035	0.187	0.442 - 0.588
Reg. Corr. Coeff's	28	0.364	0.032	0.172	0.297 - 0.431
combined	56	0.439	0.025	0.193	0.387 - 0.491
diff		0.150	0.048		0.054 - 0.247

diff = mean (Crisis Corr.Coeff's) - mean (Reg. Corr.Coeff's) t = 3.1211
$\mathbf{H_o}$: diff = 0 degrees of freedom = 70
$\mathbf{H_1}$: diff < 0 $\mathbf{H_1}$: diff = 0 $\mathbf{H_1}$: diff > 0
Pr(T < t)=0.999 Pr(T > t)=0.003 Pr(T > t)=0.001

Notes: This table shows the t-stat test result for the UK CDS correlation coefficient regimes.

The results from both tables confirm earlier results that show the evidence of contagion in Regime 1. Table 4.10 has a test statistics of 8.1093 with 70 degrees of freedom. The p-value of 0.00 suggest that we reject the null hypothesis at 5% level of significance. Therefore, we fail to reject the alternative hypothesis that regime 1 is greater than regime 2. Table 4.11 equally provides the same conclusion and therefore allowance us to conclude that there was contagion in regime 1 for both country CDS indexes. Next, we present tables that show the absence of contagion between indexes (*not between regimes*) after applying t-test on CDS correlation coefficients. Although we showed the existence of contagion between regimes, this does not hold for all index correlation coefficients within regimes. Therefore, we report those relationships that are different from our regimes conclusions.

The relationships between the indexes in tables 4.12 & 4.13 are different from regime dependent relationships. Showing that while there was generally increase in correlation coefficients between CDS indexes that allows us to draw the conclusion of contagion, there are sectors that had only interdependent relationships i.e. no increase in correlation supported by t-stat test. For example, we see that in the US the relationship between consumer goods CDS index and sovereign CDS index was interdependent in regime 1 (where most relationships where contagious) and the opposite is true for the same indexes in regime 2. Suggesting consumer index had greater correlation with sovereign at tranquil period. In the UK CDS indexes for Banks and Other financial services showed greater correlation after the crisis. This is not surprising as UK government became heavily invested within these sectors. For example, the government currently owns 62% of royal bank of Scotland with intended date of divestiture in 2025.

Table 4.12: US index Correlation

Regime 1	Coeff.	Std. Err.	t-stat	Result
corr(CSMGOODS,SOVR)	0.072	0.090	0.024	Interdependence
corr(ELECPOWER,MNFRG)	0.140	0.069	0.042	Interdependence
corr(ELECPOWER,TRNSP)	0.225	0.054	0.013	Interdependence
Regime 2				
corr(CSMGOODS,SOVR)	0.125	0.057	0.029	Contagion

Notes:These correlations coefficients show no contagion effects using t-stat results. The indexes are: Consumer goods (csm goods), Electric power (elec power), Manufacturing (manufacturing), Other financial services (other fin), Service companies (Service co), Telecommunications (Telecomm), Transport (Trsp), Sovereign (Sovr).

Table 4.13: UK index Correlation

Regime 1	Coeff.	Std. Err.	t-stat	Result
corr(BANKS,SOVR)	0.232	0.059	0.041	Interdependence
corr(CSMGOODS,SOVR)	0.215	0.059	0.051	Interdependence
corr(ELECTRICPOWER,SOVR)	0.126	0.061	0.027	Interdependence
corr(OTHERFIN,SOVR)	0.242	0.059	0.019	Interdependence
corr(TELECOMM,SOVR)	0.174	0.061	0.015	Interdependence
corr(CSMGOODS,SOVR)	0.403	0.111	0.000	Interdependence
corr(ELECTRICPOWER,SOVR)	0.301	0.121	0.013	Interdependence
corr(TELECOMM,SOVR)	0.192	0.087	0.028	Interdependence
Regime 2				
corr(BANKS,SOVR)	0.472	0.143	0.001	Contagion
corr(OTHERFIN,SOVR)	0.355	0.126	0.005	Contagion

Notes:These correlations coefficients show no contagion effects using t-stat results. The indexes are: Consumer goods (csm goods), Electric power (elec power), Manufacturing (manufacturing), Other financial services (other fin), Service companies (Service co), Telecommunications (Telecomm), Transport (Trsp), Sovereign (Sovr).

For the purposes of robustness checks of the above model, we ran a DCC-Garch model, this time choosing the dates between the two regimes base on when regulation was introduced and the date set by national and international regulatory agencies for full compliance with these regulations. This is similar to process applied by Kalbaska and Gątkowski (2012) when looking at contagion from CDS market in Eurozone. Where they exogenously imposed dates based on empirical understanding. We recognise that this is often a contentious issue, i.e. assigning both the start and end dates e.g. in recent studies of the subprime crisis by Longstaff (2010). He uses the calendar year of 2007 as the crisis period, while many others use a later start date of July or August of that year (see: Duffie et al., 2015, Guidolin and Pedio, 2017, Hatemi-J and Roca, 2011). However, given that our analysis is focused on regulation and these regulations have both announcement dates and compliance dates provides us sufficient justification to apply these dates (2007-2013 & 2014-2019) exogenously.

4.6.2 DCC-GARCH

Tables below provides us results between the period from when crisis occurred and the announcement of regulation for all derivatives markets. Therefore covering the period of high volatility that is consistent with our correlation results and Regime 1 discussed earlier. Figure 4.3, shows results from US CDS indexes. The mean equation (μ, panel A) shows that all coefficients are statistically significant for all indexes except Sovereign CDS index. It also shows CDS indexes coefficients to all be negative, this is consistent with the effects of the crisis, volatility and results from earlier analysis. Figure 4.3 mean equation results of UK CDS indexes also show the same pattern with the exception that the Sovereign CDS index is significant at the 10% level.

The variance equation in both Tables below consist the constant term (ω), the Arch (α) and Garch (β) effects coefficients. The result are all statistically significant. Indicating that the volatility persistence measure (α+β) was close to one for all the CDS indexes examined. These results show that the volatility in the GARCH models displayed high persistence. This is similar to the result of MS-VAR regime persistence probability earlier discussed. The last two rows of Panels in tables report the estimates of the DCC parameters a and b. Both parameters are statistically significant, revealing a substantial time-varying co- movement. Moreover, the conditional correlations also exhibited high persistence, with the average sum of the two coefficients being over 0.90 during the sample period.

Figure 4.3: US regime 1 DCC-Garch result

DCC-GARCH model (US Regime 1)										
	TELECOM	BANKS	CSMGOODS	ELECPOWE	MNFG	OTHERFIN	SERVICEC	SOVR	ENERGYCO	TRNSP
	Panel A: Mean Equation									
μ	-2.604***	-	-1.072***	5.956***	-	-5.262***	-3.068**	-0.233**	-1.145***	-6.612*
	(0.364)	(0.418)	(0.263)	(2.200)	(0.240)	(1.082)	(0.410)	(0.156)	(0.225)	(2.143)
	Panel B: Variance Equation									
ω	6.347***	7.986***	18.657***	1517.764***	13.946*	154.961	10.607***	1.525***	6.504***	740.048***
	(1.998)	(3.549)	(3.582)	(138.003)	(1.905)	(37.141)	(1.913)	(0.522)	(1.960)	(192.545)
α	0.196***	0.713***	0.304***	1.806***	0.449***	0.232***	0.241***	0.186***	1.835***	0.709***
	(0.031)	(0.066)	(0.055)	(0.291)	(0.029)	(0.050)	(0.032)	(0.054)	(0.258)	(0.139)
β	0.789***	0.568***	0.471***	-0.003***	0.529***	0.657***	0.773***	0.734***	0.260***	0.372***
	(0.025)	(0.043)	(0.069)	(0.001)	(0.029)	(0.060)	(0.019)	(0.069)	(0.040)	(0.069)
	Panel C: Multivariate DCC equation									
a	0.071***									
	(0.017)									
b	-0.050***									
	(0.002)									

Note: Table shows US regime 1 DCC-Garch result. Standard errors are shown in parenthesis while ***, ** * represent 1%, 5% 10% significance level of respectively.

Figure 4.4: UK regime 1 DCC-Garch result

DCC-GARCH model (UK Regime 1)								
	TELECOMM	BANKS	CSMGOODS	ELECTRICPOWER	MNFG	OTHERFIN	SERVICECO	SOVR
	Panel A: Mean Equation							
μ	-1.755***	-1.191***	-0.631***	-0.574***	-1.340***	-0.923***	-1.069***	-0.248*
	(0.355)	(0.488)	(0.131)	(0.229)	(0.200)	(0.227)	(0.257)	(0.145)
	Panel B: Variance Equation							
ω	10.398***	25.409***	1.411***	1.637***	0.662*	0.395	3.687***	0.519***
	(2.407)	(8.054)	(0.334)	(0.493)	(0.364)	(0.258)	(0.826)	(0.126)
α	0.457***	0.334***	0.554***	0.605***	0.725***	0.227***	0.293***	0.426***
	(0.074)	(0.072)	(0.086)	(0.088)	(0.089)	(0.033)	(0.047)	(0.057)
β	0.598***	0.563***	0.571***	0.662***	0.574***	0.796***	0.691***	0.700***
	(0.031)	(0.079)	(0.043)	(0.032)	(0.030)	(0.020)	(0.036)	(0.026)
	Panel C: Multivariate DCC equation							
a	0.058***							
	(0.014)							
b	0.634***							
	(0.069)							

Note: Table shows the UK regime 1 DCC-Garch result. Standard errors are shown in parenthesis while ***, ** * represent 1%, 5% 10% significance level of respectively.

Tables 14 15 present the results that cover the period when regulation was fully phased-in. The tables display results that show that Variance equation results are mostly not statistically significant. These results are largely consistent with what we expected from the sample period, as regulation meant little volatility as compared to the previous period. However, the mean equation panel shows all indexes to be positively affected. This shows that regulation has positively impacted the CDS indexes. However, when we compare it to MS-VAR results, the positive mean results of both tables are less than the results shown by the MS-VAR result. An explanation for this might be that although regulation was fully phased in 2014, most organisations likely met these requirements much earlier; therefore, our Garch model has not fully captured this impact due to the exogenous application of Regimes. Finally, we test the application of the DCC model that reduces to the CCC model when the adjustment parameters that govern the dynamic correlation process are jointly equal to zero. We perform a Wald test to test this hypothesis with results that support the application of the model (i.e. chi2 (2) = 12.54 Prob > chi2 = 0.0019).

Figure 4.5: US regime 2 DCC-Garch result

DCC-GARCH model (US Regime 2)										
	TELECOMM	BANKS	CSMGOODS	ELECPOWER	MNFG	OTHERFIN	SERVICECO	SOVR	ENERGYCO	TRNSP
Panel A: Mean Equation										
μ	0.316	-0.340**	-0.050	-0.861***	-0.286	-0.516	-0.800*	-0.054	-0.327	-0.199
	(0.520)	(0.164)	(0.142)	(0.268)	(0.270)	(1.121)	(0.476)	(0.036)	(0.469)	(0.228)
Panel B: Variance Equation										
ω	5.929***	10.601***	3.976***	6.770***	3.761***	240.272***	14.083***	0.058***	21.760***	0.284***
	(1.879)	(2.279)	(2.789)	(1.788)	(0.773)	(49.409)	(5.144)	(0.020)	(4.568)	(0.093)
α	0.678***	0.163***	0.061	0.387***	0.418***	0.289***	1.429***	0.500***	1.889***	0.049***
	(0.155)	(0.050)	(0.056)	(0.157)	(0.082)	(0.073)	(0.224)	(0.086)	(0.257)	(0.009)
β	0.648	0.047*	0.521***	0.614***	0.639*	0.184***	0.432***	0.637***	0.177***	0.937***
	(0.050)	(0.172)	(0.318)	(0.064)	(0.040)	(0.114)	(0.029)	(0.039)	(0.045)	(0.008)
Panel C: Multivariate DCC equation										
a	0.045***									
	(0.017)									
b	0.198									
	(0.231)									

Note: Table shows US regime 2 DCC-Garch result. Standard errors are shown in parenthesis while ***, ** * represent 1%, 5% 10% significance level of respectively.

Figure 4.6: UK regime 2 DCC-Garch result

DCC-GARCH model (UK Regime 2)								
	TELECOMM	BANKS	CSMGOODS	ELECTRICPOWER	MNFG	OTHERFIN	SERVICECO	SOVR
	Panel A: Mean Equation							
μ	-0.098	-0.433*	0.102	-0.214	-1.045***	-0.166	-0.299	-0.103
	(0.443)	(0.239)	(0.156)	(0.191)	(0.351)	(0.130)	(0.215)	(0.076)
	Panel B: Variance Equation							
ω	57.266***	2.044***	2.196***	3.640***	22.481***	0.981***	11.478***	0.063***
	(9.108)	(0.722)	(0.650)	(0.839)	(3.758)	(0.252)	(1.851)	(0.031)
α	0.207***	1.219***	0.207***	0.093***	1.541***	0.233***	0.414***	0.086***
	(0.066)	(0.153)	(0.055)	(0.031)	(0.532)	(0.049)	(0.083)	(0.021)
β	0.163	0.457***	0.628***	0.679***	-0.002	0.668***	0.112***	0.902***
	(0.113)	(0.032)	(0.078)	(0.068)	(0.005)	(0.052)	(0.092)	(0.021)
	Panel C: Multivariate DCC equation							
	0.042							
a	(0.010)							
	0.821***							
b	(0.036)							

Note: Table shows the UK regime 2 DCC-Garch result. Standard errors are shown in parenthesis while ***, ** * represent 1%,5% 10% significance level of respectively.

4.6.3 Impulse Response Functions

The last part of this analysis deals with establishing the channels of contagion. In this subsection, we trace the time paths of the invoked responses of CDS indexes after economic shocks are imposed on the system. This exercise allows us to identify the sign of association between the variables and the respective market response paths over time as they explicitly reveal the interaction between these markets and the dynamic process of the interaction. To achieve this objective, we apply the regime-dependent impulse response function suggested in Ehrmann et al. (2003), which analogously describes the relationship between endogenous variables and fundamental disturbances within each Markov switching regime.

Since impulse responses trace the paths of different variables when they return to equilibriums after a shock is injected to the system, the visual aids provided by the impulse response functions are useful when the full impacts of economic shocks on an economic system take long lags. In each case, the shock to each equation is equal to one standard deviation of the equation residual, and the impulse responses of all the variables to the shock are traced out for a period of 10 weeks. As such, it facilitates our comparison of the variable responses after different shocks hit the economy in two distinct regimes. This is an advantage of the non-linear VAR model; it incorporates the asymmetric effects of economic shocks on the economic system across different regimes.

The impulse responses of CDS index to various shocks (from the crisis or changes from regulation) imposed are presented in the tables below. Responses are divided between the two Regimes for both countries (i.e. US and UK). Some dissimilarities between the 2 Regimes stand out. Overall, CDS indexes are more responsive to economic shocks in the “risky” Regime (Regime 1). For instance, as shown in US Regime 1, most of the index Y-axis that shows the % which an index response to a shock ranges from a sharp drop of 120% to -80%. Highlighting the impact of the crisis on these indexes. While the Y-axis for US Regime 2 indexes ranges from a moderate drop of 20% to -20%. The same pattern is exhibit in the UK index response functions. Where Regime 1 has Y-axis that dropped from 16% to -4%, while Regime 2 highest impulse is 12% and lowest of 4%.

Generally, responses emanating from CDS index own shocks are found have the most impact. Looking at US Regimes IRFs, the Banking CDS index in Regime 1, in response to its own shock, dropped from a peak of about 25% to about -3% from week one to week 2 and further to its lowest level in week 5 to approximately 6%. Compare this to Regime 2, where it dropped from 4% in week 1 to -1% in week 2 and returned to about a base of zero, exhibiting stability consistent with the introduction of regulation. By comparison, UK Regime 1 Banks CDS index jumped from 13% in week 1 to -1% in week 2. Whereas in Regime 2 the Banks CDS index response due to its own shock, was 9% in week one to about 1.6% in week 2.

The indexes found to exhibit the highest jumps in US Regime 1 are Transportation, Electric Power and Other Financial Companies. They show a jump between the first and the second week of 63% to -13%, 57% to -17% and 28% to -6% respectively. These same indexes in Regime 2 show changes between the first and second week from 9.5% to -1.2%, 5.7% to 1.2% and 20% to -15% respectively. Service Companies and Telecommunications CDS indexes are the most affected with respect to impact of other indexes on them other shocks from their lags. For example, Service Companies CDS index moved from 11% in week 1 to -4.8% in week 7. However, it was being impacted by: Banking index at 9.9% in week to -2.3% in week 6, Manufacturing at 9.3% in week 1 to - 3.7% in week 10, Consumer Goods at 9% in week 1 to -1.6% in week 9 and by Transportation with 9.7% in week 1 to -3.2 in week 9. On the other hand, Sovereign CDS index is the least respondent to shocks from the system. It changed as a result of lag shock from 3% on week 1 to 0 by week 2, thereafter remained between 0% and 1%. While other shocks remain between 1% to -0.5% throughout. These patterns generally stayed the same in Regime 2, i.e. the most and least affected indexes, however as highlighted earlier these shocks are almost non-existent (other than fluctuations between 1% to -1%) due to stability/effects of regulation in Regime 2 (with exception to index lags effects).

In the UK the indexes that exhibit the highest jumps in Regime 1 are; Banking and Other Financial Companies. They jumped from 13% in week 1 to to -2% in week 6, and 14% in week 1 to -0.5% in week 2 respectively. Furthermore, the Banking index exhibited the highest impact on Other Financial

Companies index from 4% in week 1 to -2% in week 4. This is greater than the impact of its lag and more lasting. Manufacturing CDS index also moved from 15% in week 1 to 0.6% by week 8, with Electric Power Index impacting it from 2% in week to -3.6% by week 4. The indexes that were least affected in UK Regime 1 were Consumer goods, Service companies, Telecomms and Sovereign CDS indexes. They show a jump from week 1 to 2 by; 5% to -0.5%, 6% to 0%, 5.4% to -1% and 6.4% to 0% respectively. In Regime 2, IRFs show a large stability effects. Almost all indexes movement remaining between 1% to -0.5% with the exception of Banking index that moved from 10% in week 1 to -2.4% in week 4 (although still less than jumps in Regime 1) and Sovereign index that showed the least movement from 1.9% in week 1 to -0.34% in week 2. Reactions of CDS indexes to the Banking and Other Financial Companies CDS indexes shocks play the most important role in the CDS market variations. In a similar fashion, the impulse responses of CDS indexes to the Sovereign CDS provided stability effects and remained least affected by its lag shock throughout the 10 weeks period.

4.7 Conclusion

The 2007 subprime crisis provides an ideal opportunity for studying the effects of contagion at Sector level within the whole economy. We use data from CDS indexes to examine whether contagion occurred across various sectors and if the introduction of regulation resulted in changing this relationship to interdependence. This was motivated by the frequently adopted definition of contagion in the literature as a significant temporary increase in cross-market linkages after a major distress event.

We employ a MS-VAR methodology that allows us to assess pairwise relationships across various CDS index of the whole system. Using weekly data of 10 CDS sector indexes in the US and 8 CDS sector indexes in the UK from January 2007 through January 2020 we investigated the existence of contagion and the impact of regulation. We then used IRFs to show channels of contagion between sector indexes.

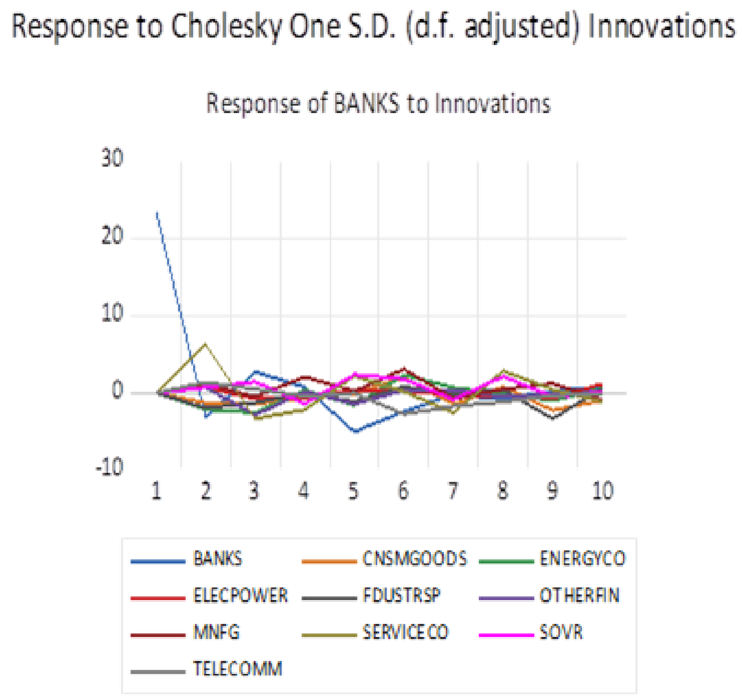
The results from the Markov switching VAR specification reveal the existence of two Regimes in our data and that there was contagion effects among these CDS indexes that changed to interdependence due to the introduction of regulation. This is consistent with the results of Longstaff (2010) that showed the existence of contagion between subprime collateralized debt obligations (CDOs) indexes in the US. These are yet another form of derivative instruments, further supporting the implementation of regulation. On the other hand, Flavin and Sheenan (2015) did not find contagion effects between mortgage back securities and other financial instruments. However, their result show contagion between liquid instruments. This also supports our choice of liquid CDS in the analysis. Guo et al. (2011) also confirmed the existence of contagion between stock market, real estate market, credit default market, and energy market. We also found the duration of a “stable” Regime to be longer than that of a “volatile” Regime. This finding is consistent with the empirical observation that the durations of economic stability tend to be longer than those of economic crisis. Our results are similar to the findings of Guo et al. (2011).

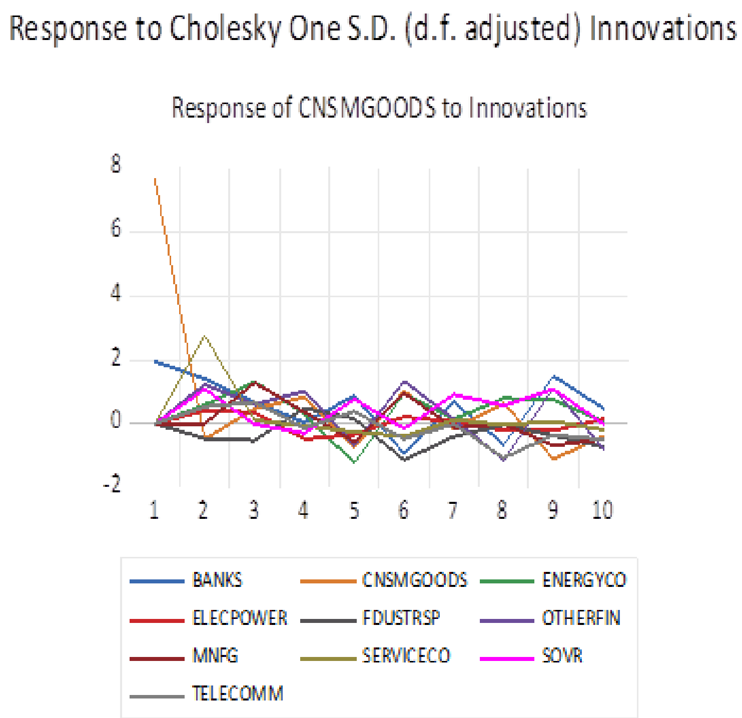
A number of striking findings emerge from the study. Firstly, we find the use of CDS was economy wide, i.e. most of the sectors in the economy were heavily involved in the use of CDS instruments in some way (as opposed to the view we held that it was mostly within the financial sector). The results show that there was widespread contagion within CDS indexes in the period of the crisis and prior to implementing regulation and the relationship changed significantly to Interdependence after the introduction of regulation. Secondly, the results show that in the US the sectors that were most affected by contagion effects are Telecomms and Transportation, with Banks and Other Financial Services experiencing lesser contagion impact (this is also contrary to the general assumption). While in the UK, most affected sector were Banks, Manufacturing and then Other Financial Services. Note that our results does not provide the source of this contagion, rather the most affect sectors as a result of the contagion. We then performed robustness checks, using Garch model we consistently found the evidence that supports our initial results.

Assessment of the relationships between the CDS indexes Regime- dependent impulse response functions reveals that they all respond more significantly to various economic shocks in the “risky” Regime. That is, the contagion effects among indexes is prominent during the financial crisis. Our findings have important implications for policymakers regarding the amplified contagion effects among the sectors during financial crisis, to avoid lack of oversight. In particular, they should monitor the use of CDS from the sectors that displayed most impact of contagion.

4.8 INDEX

4.8.1 US REGIME 1 IRFs

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Response of CNSMGOODS to Innovations
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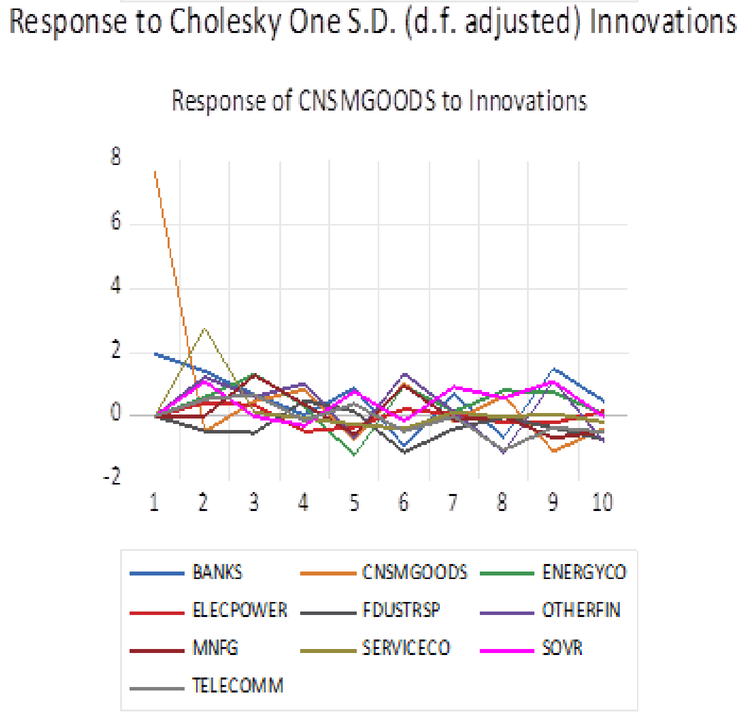
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Response of CNSMGOODS to Innovations
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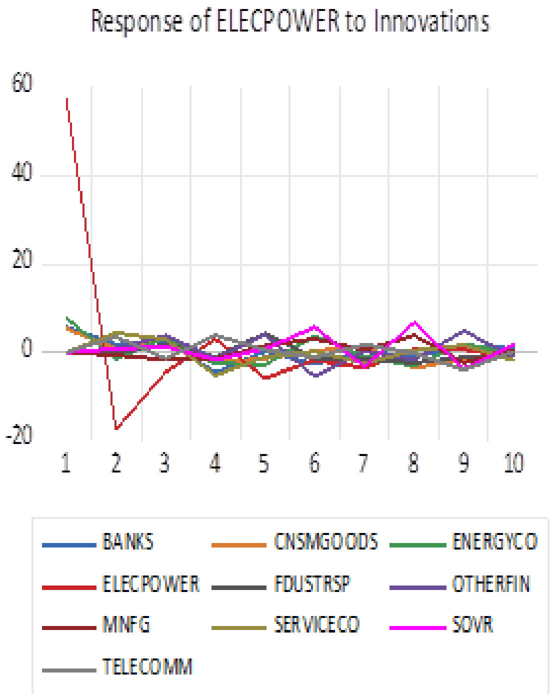

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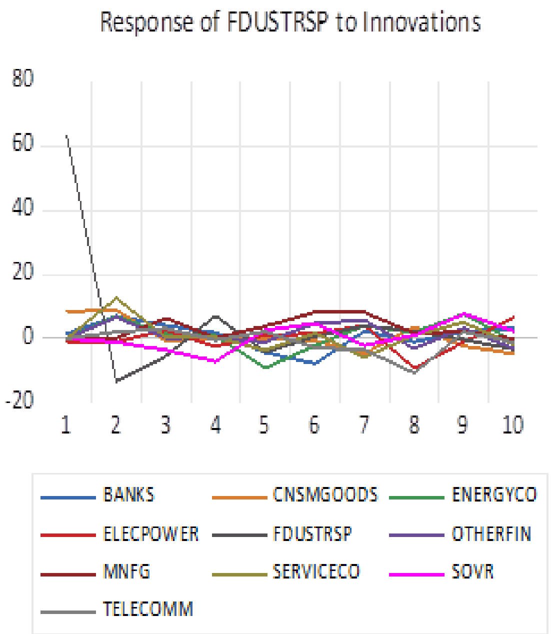

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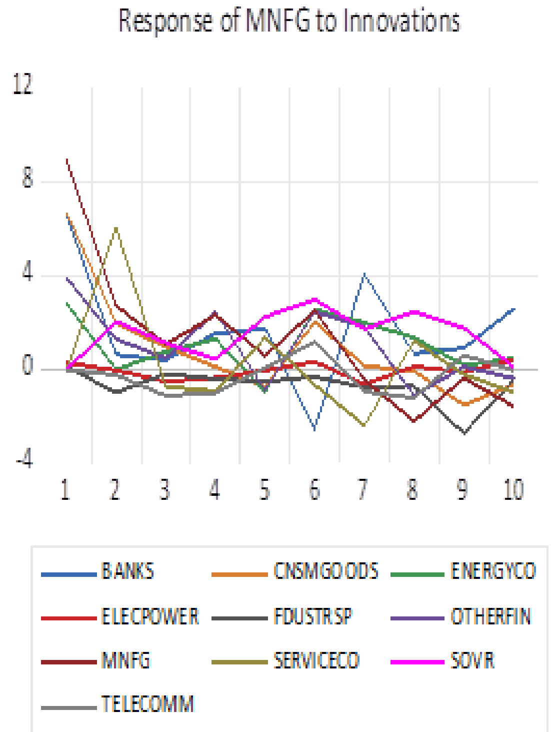

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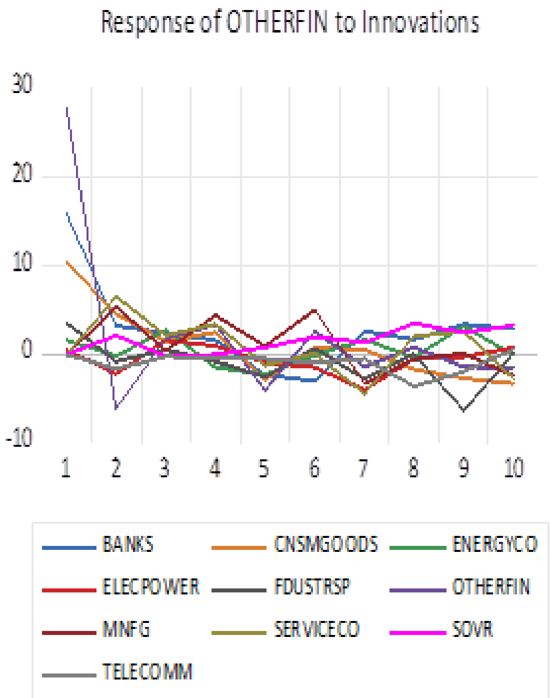

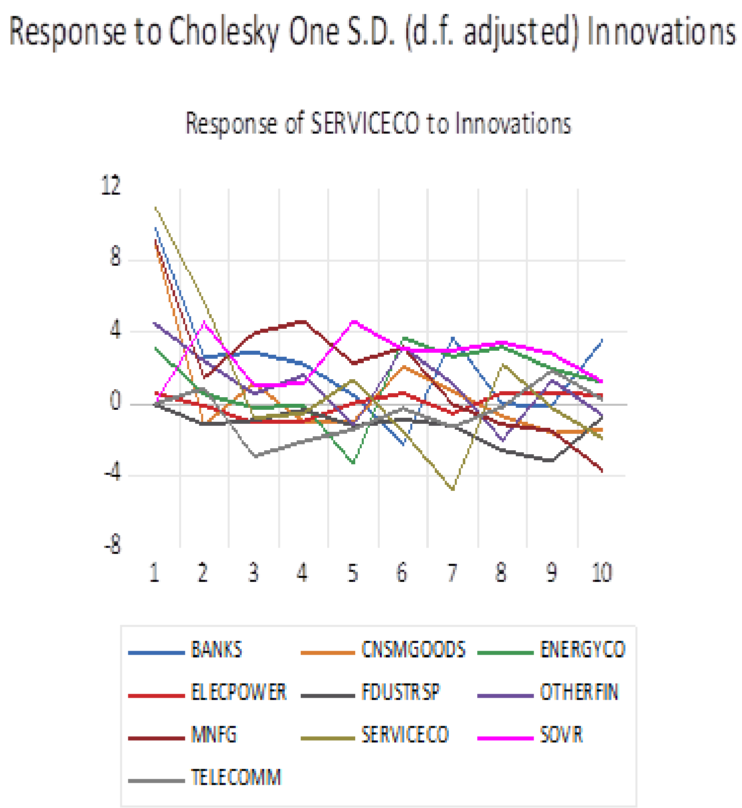
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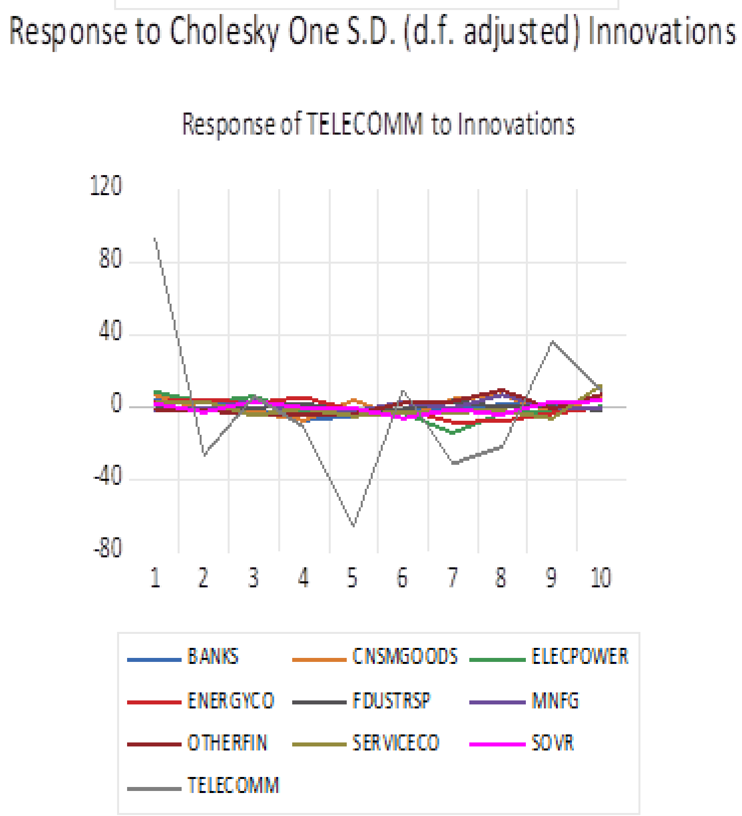
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TELECOMM

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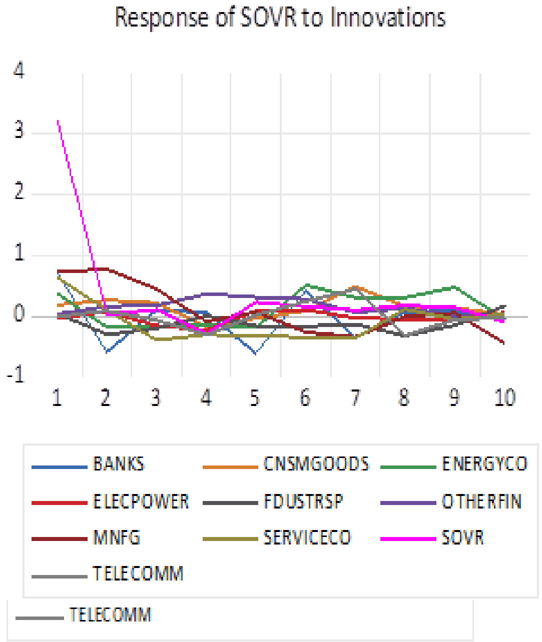
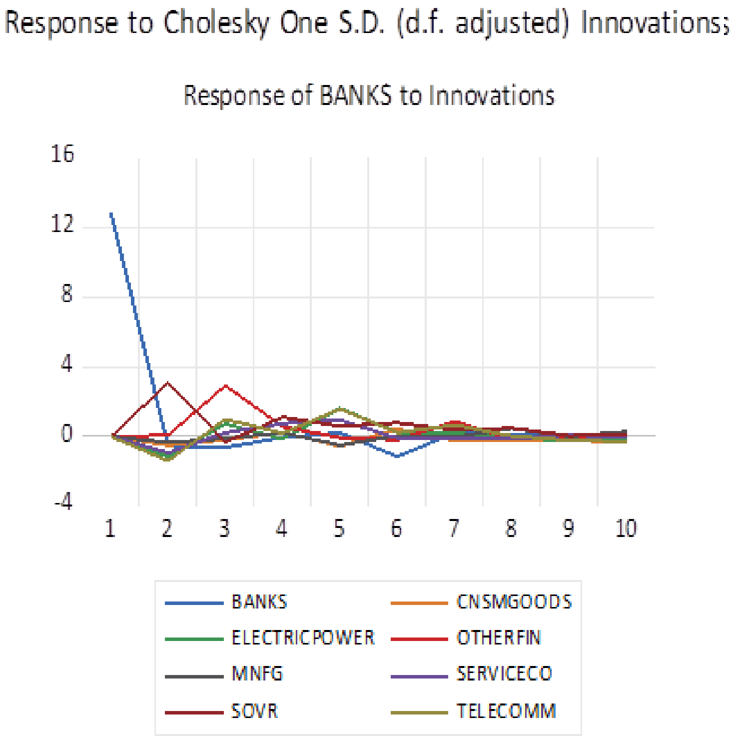
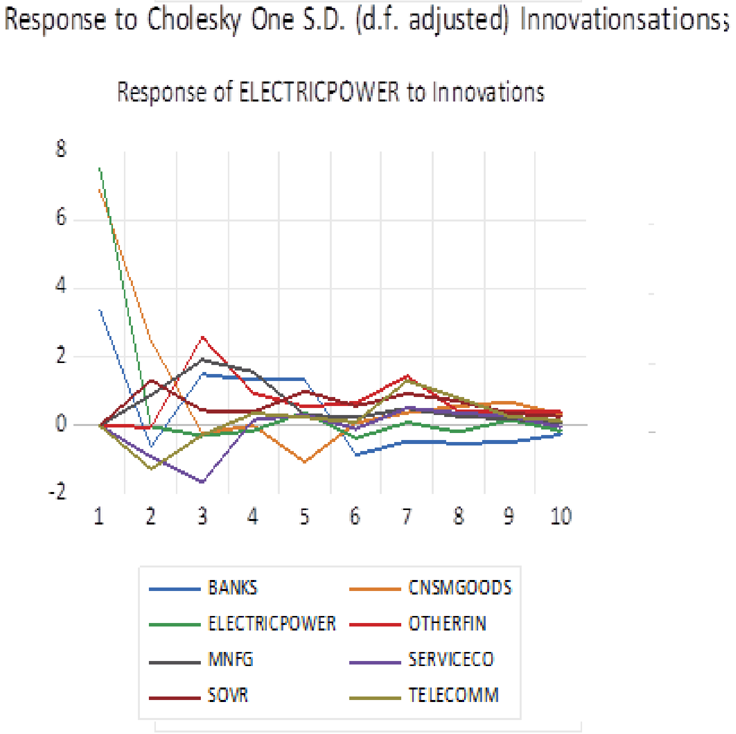


4.8.2 UK Regime 1 IRFs





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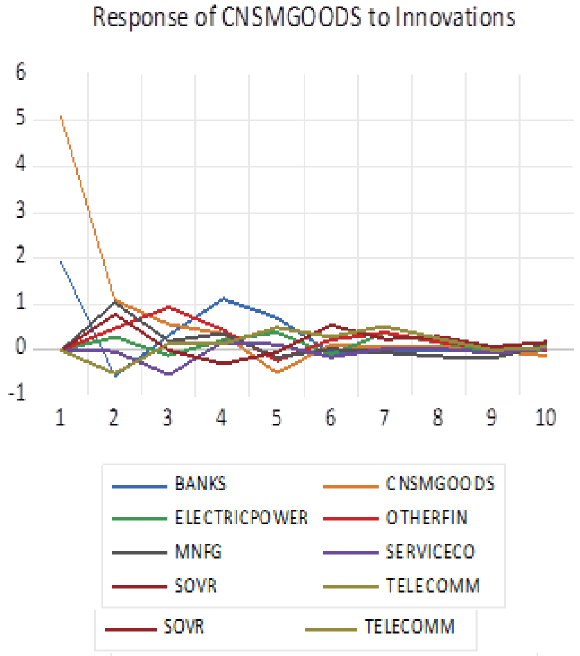

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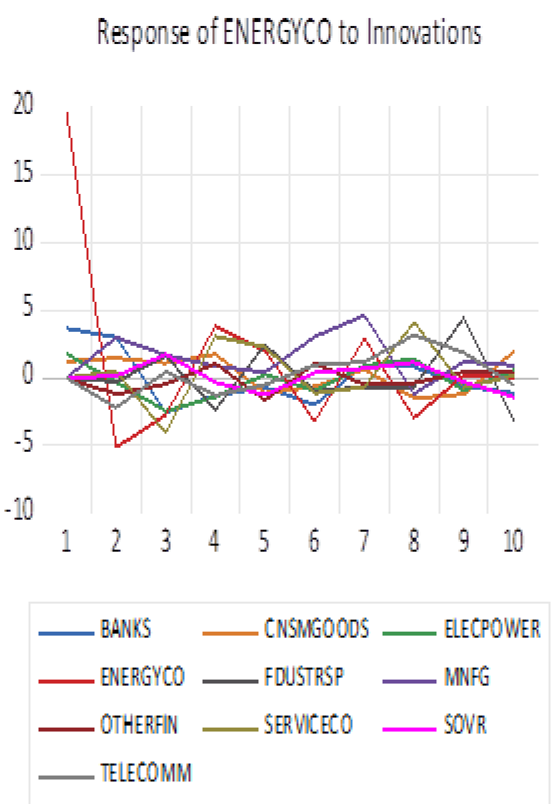
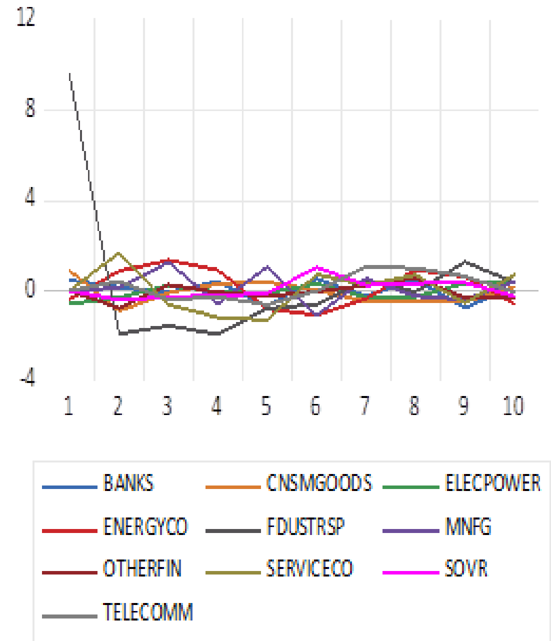


Response to Cholesky One S.D. (d.f. adjusted) Innovations

Response of FDUSTRSP to Innovations



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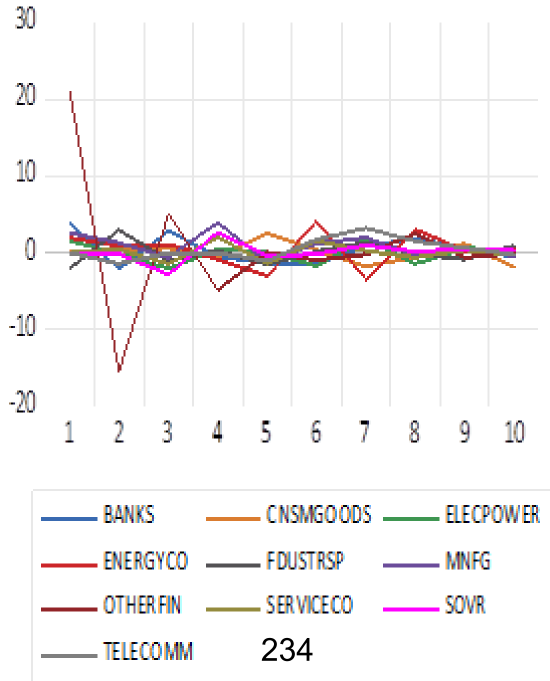
Response of OTHERFIN to Innovations



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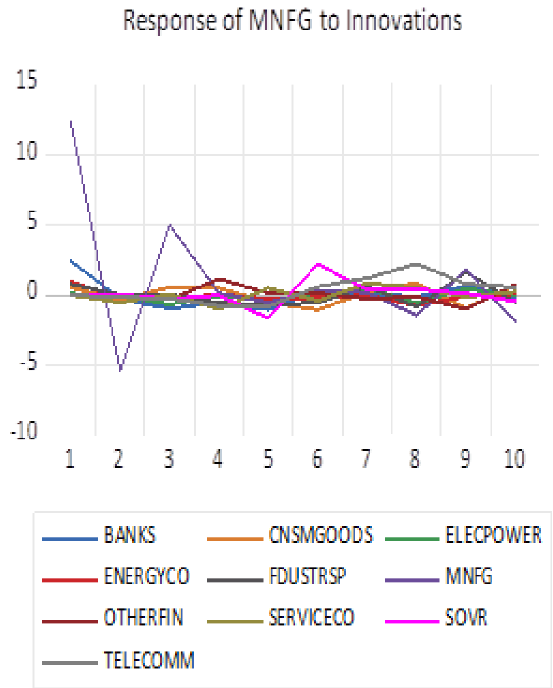
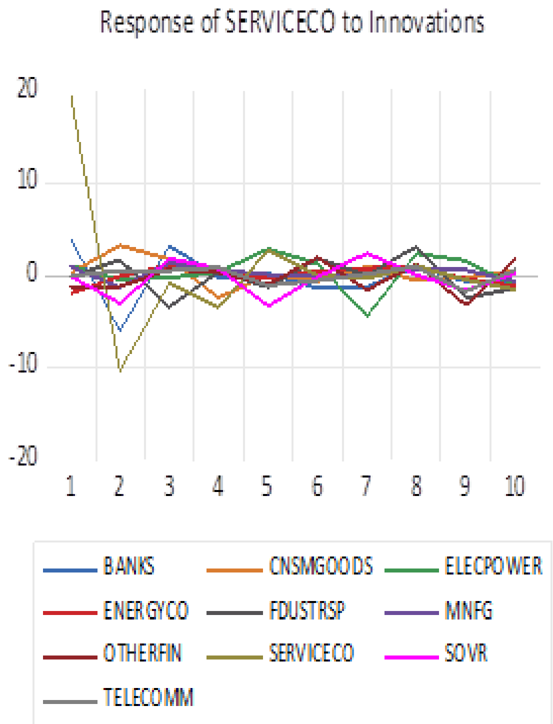
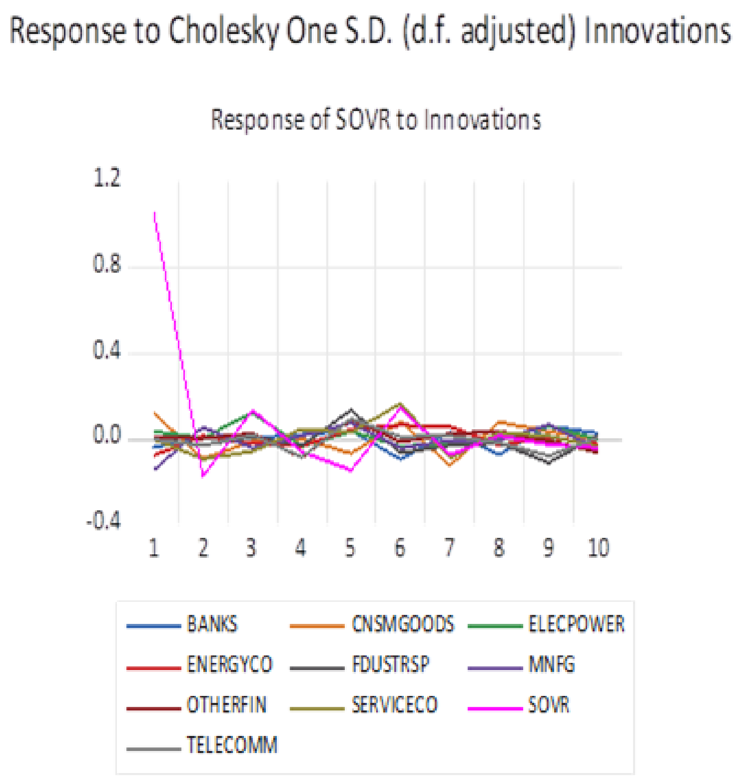


Response to Cholesky One S.D. (d.f. adjusted) Innovations



4.8.3 US Regime 2 IRFs



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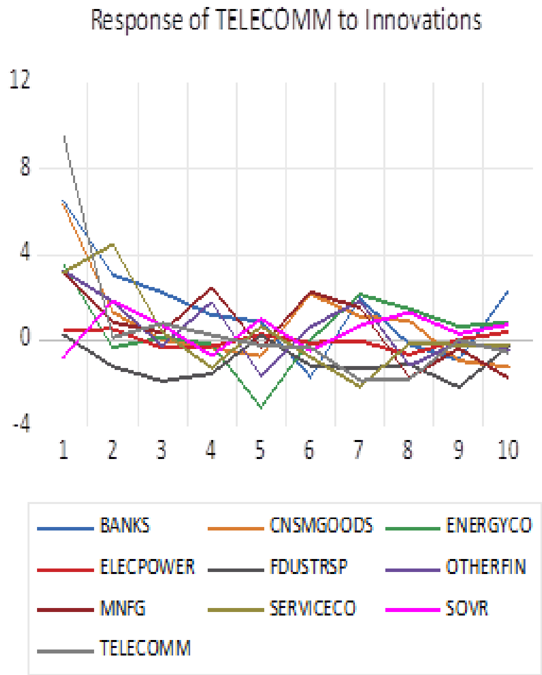

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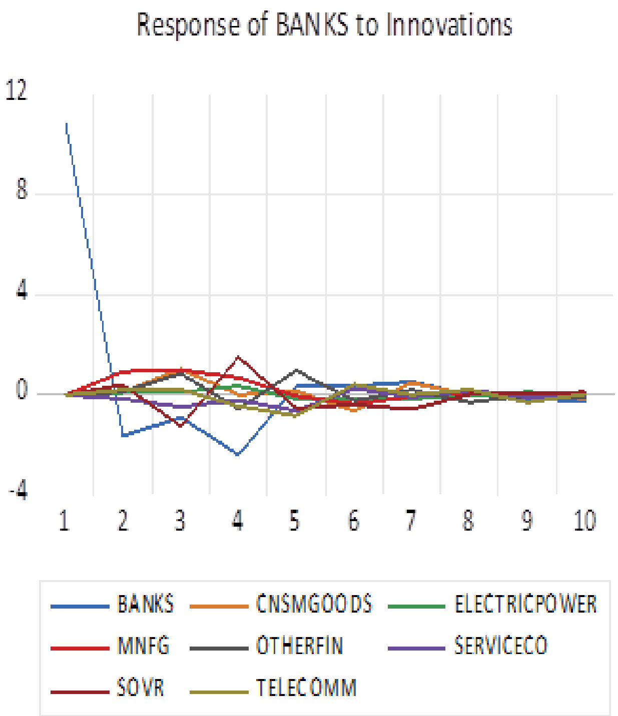
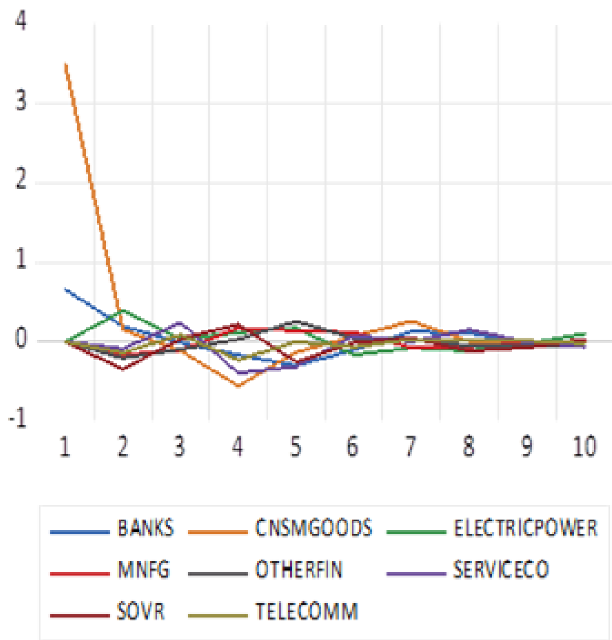


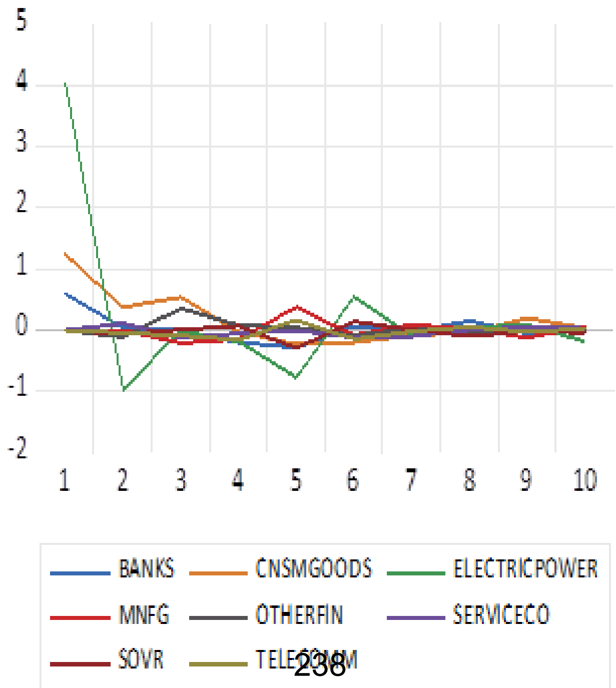
Response to Cholesky One S.D. (d.f. adjusted) Innovations

Response of CNSMGOODS to Innovations



Response to Cholesky One S.D. (d.f. adjusted) Innovations

Response of ELECTRICPOWER to Innovations



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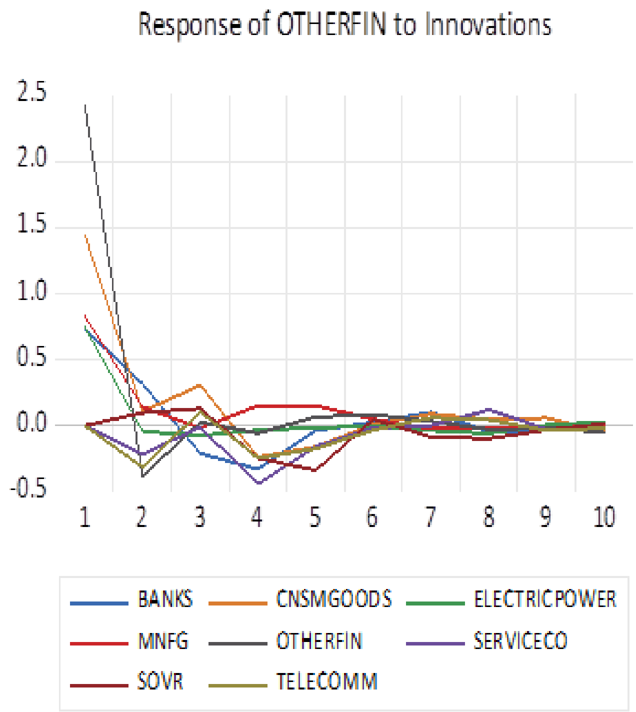

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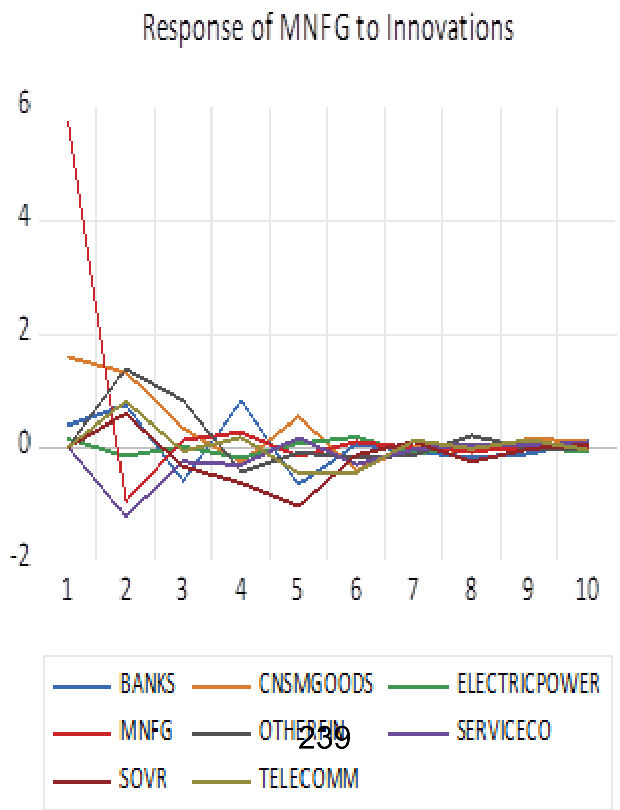

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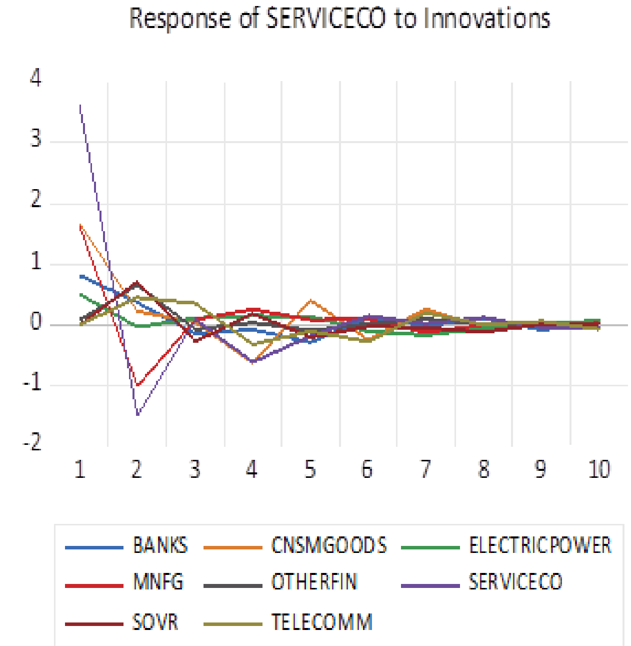

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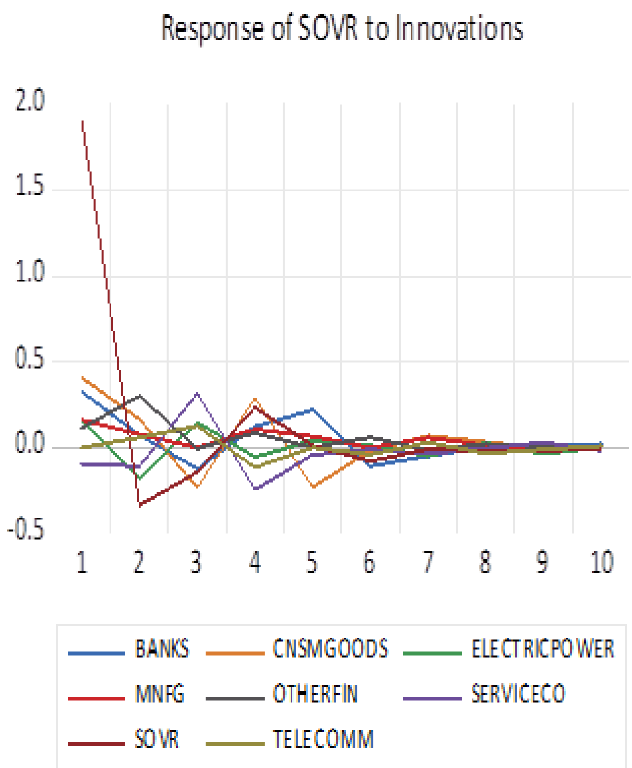
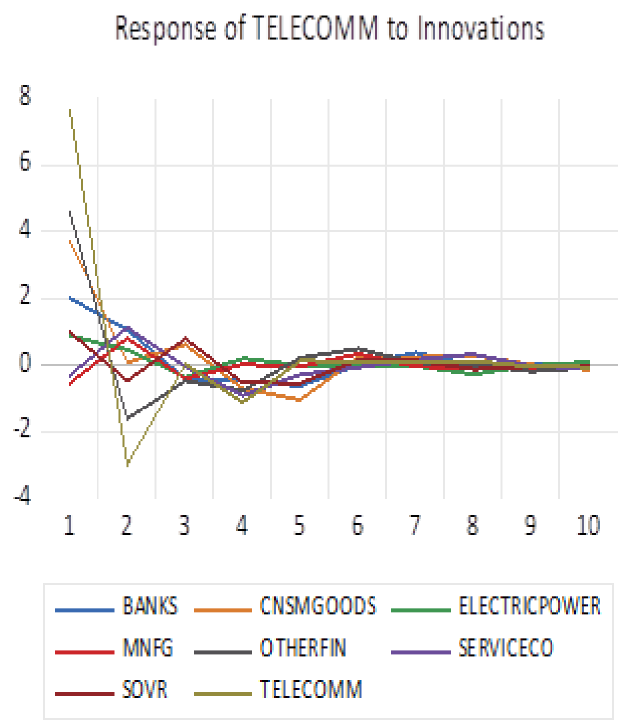
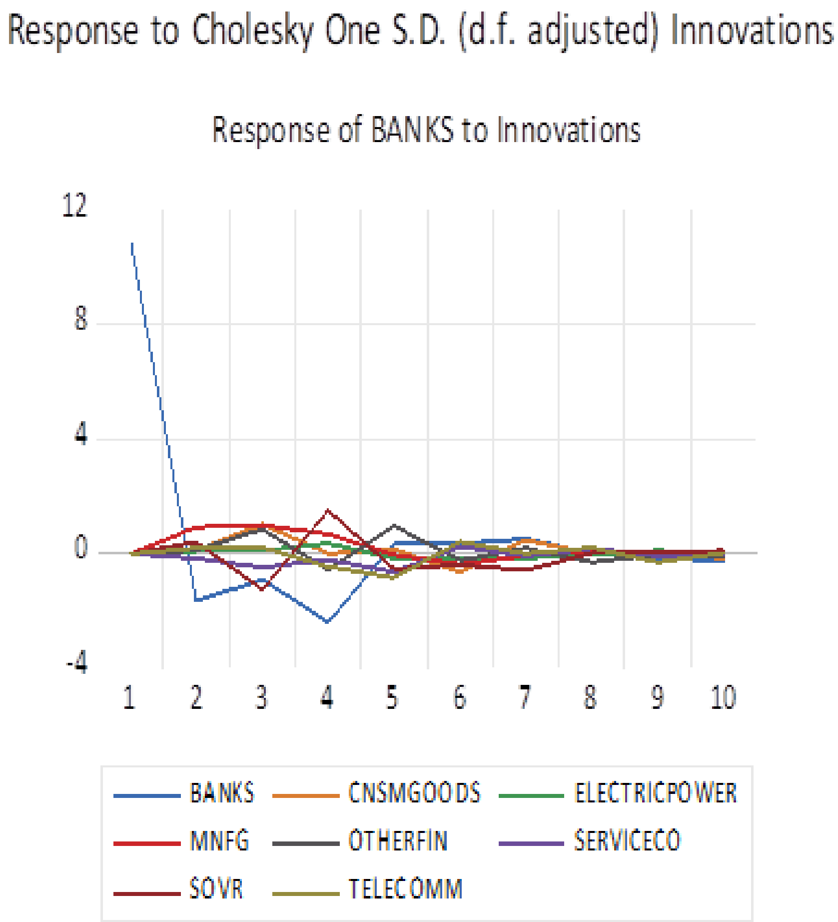
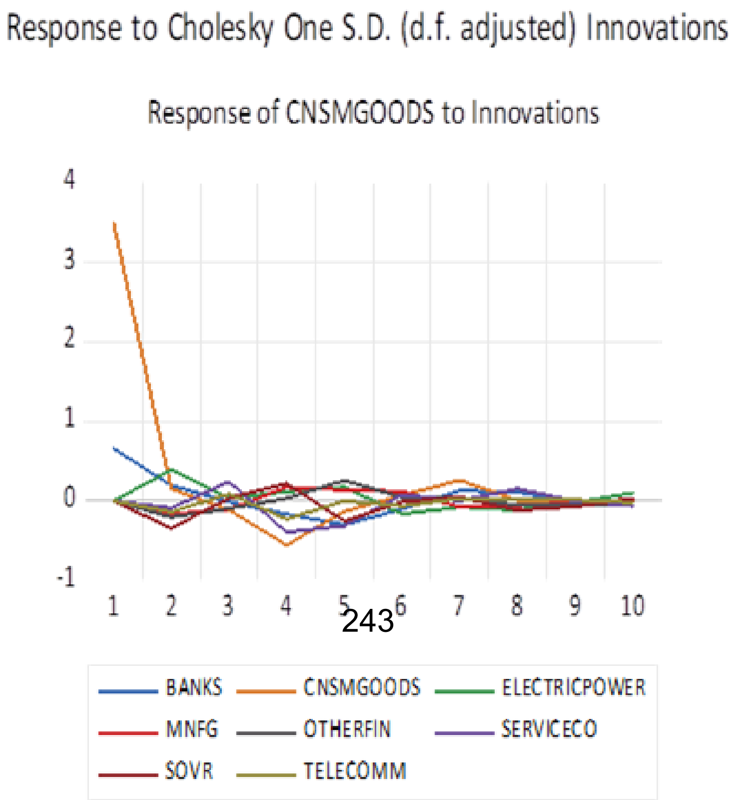


Response to Cholesky One S.D. (d.f. adjusted) Innovations



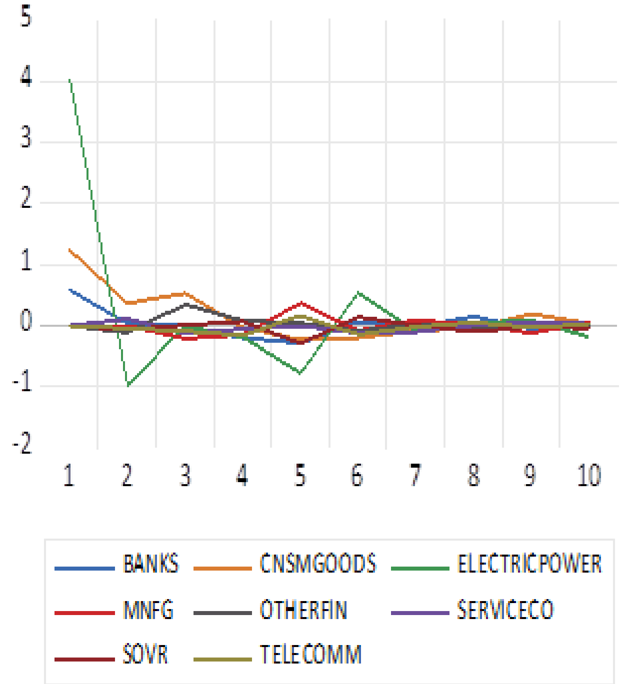
4.8.4 UK Regime 2 IRFs





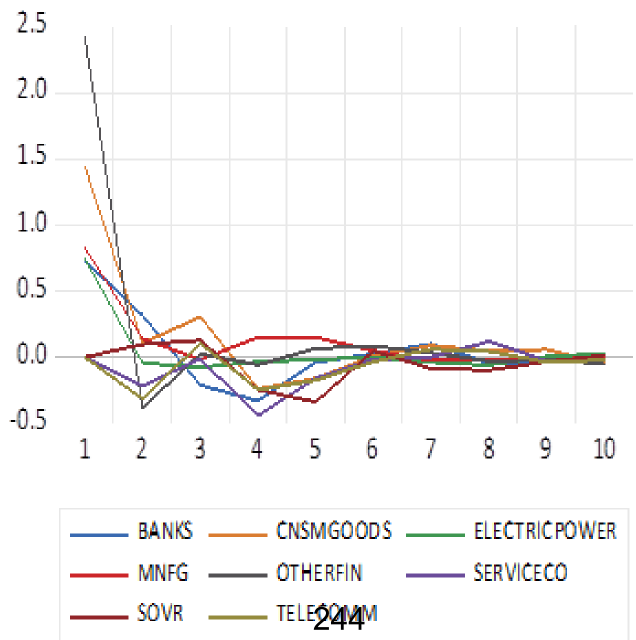
Response to Cholesky One S.D. (d.f. adjusted) Innovations

Response of ELECTRICPOWER to Innovations

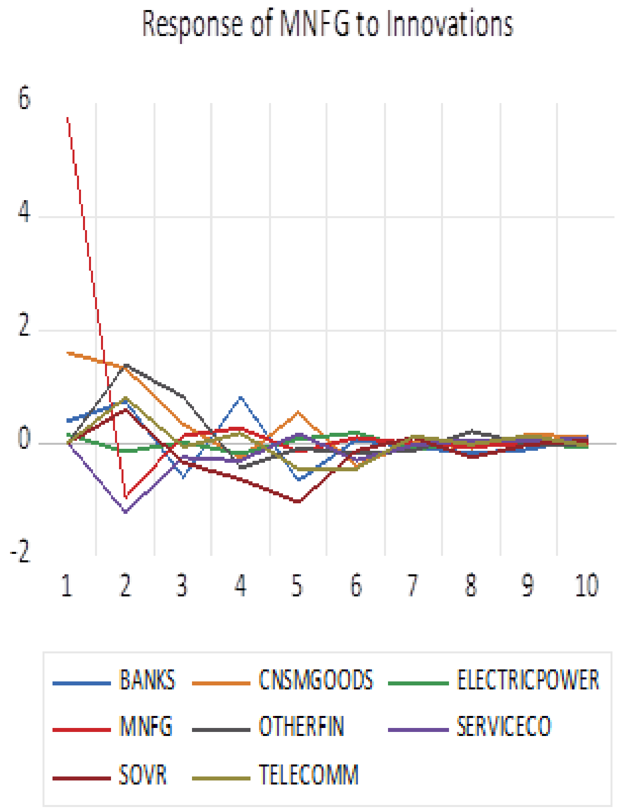


Response to Cholesky One S.D. (d.f. adjusted) Innovations

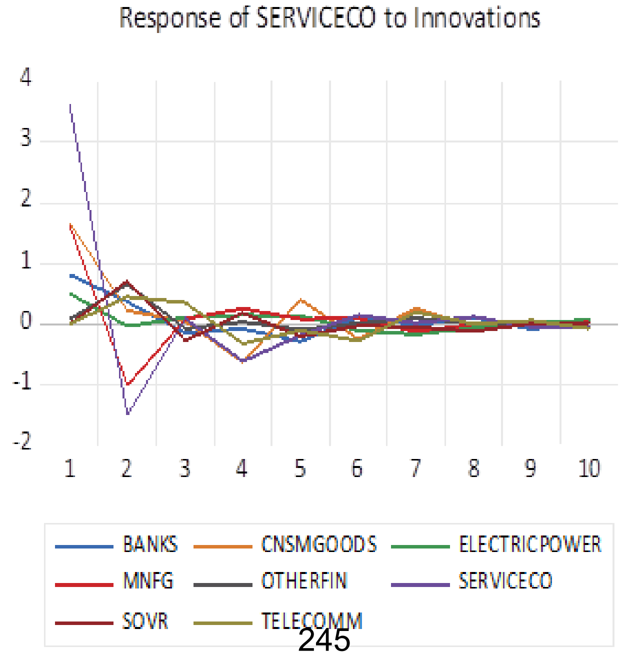
Response of OTHERFIN to Innovations



Response to Cholesky One S.D. (d.f. adjusted) Innovations

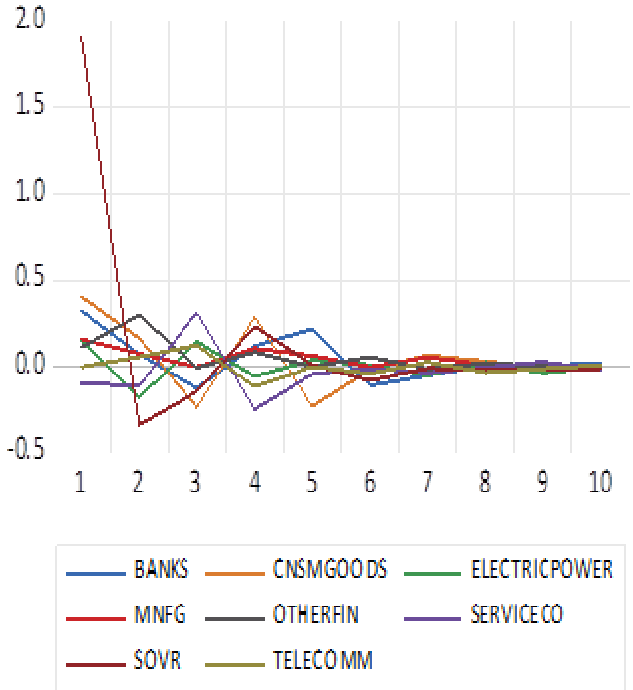


Response to Cholesky One S.D. (d.f. adjusted) Innovations



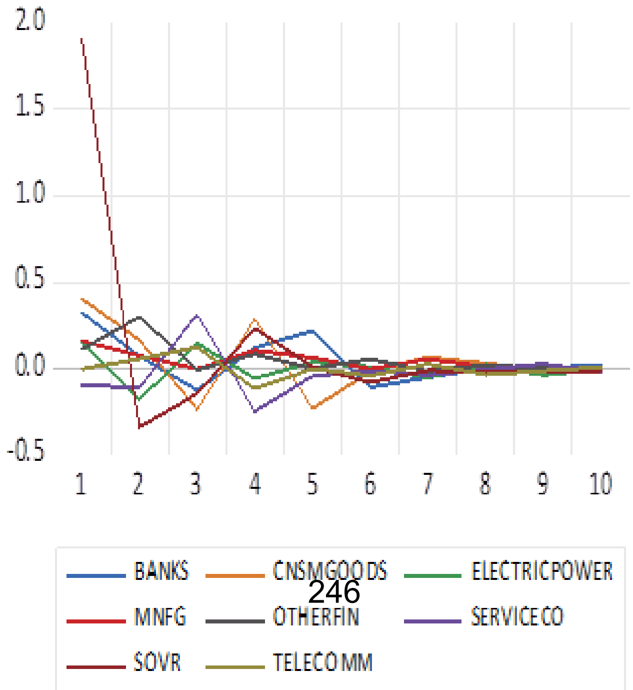
Response to Cholesky One S.D. (d.f. adjusted) Innovations

Response of SOVR to Innovations



Response to Cholesky One S.D. (d.f. adjusted) Innovations

Response of SOVR to Innovations



4.8.5 FULL NAMES OF CDS INDEX

CDS INDEX	**Full names and Mnemonics (Eikon-Refinitiv DataStream)**
US BANKS	US Banking CDS index. DSNBS5
US CSM GOODS	US Consumer Goods CDS index. DSNCG5
USELEC POWER	US Electric CDS index. DSNEP5
US ENERGY CO	US Energy CDS index. DSNEC5
US MNFG	US Manufacturing CDS index. DSNMF5
US OTHER FIN	US Other Financial Institutions CDS index. DSNOF5
US SERVICE CO	US Services CDS index. DSNSC5
US TELECOMM	US Telecommunications CDS index. DSNTL5
US TRSP	US Transportation CDS index. DSNTR5
US SOVR	US Sovereign CDS index. USV5EAC
UK BANKS	UK Banking CDS index.DSUBK5E
UK CSM GOODS	UK Consumer Goods CDS index. DSUCG5E
UKELEC POWER	UK Electric Power CDS index. DSUEP5E
UK MNFG	UK Manufacturing CDS index. DSUMF5E
UK OTHER FIN	UK Other Financial Institutions CDS index. DSUOF5E
UK SERVICE CO	UK Services CDS index. DSUSC5E
UK TELECOMM	UK Telecommunications CDS index. DSUTL5E
UK SOVR	UK Sovereign CDS index. GBG5EAC

Chapter 5

Conclusion

5.1 Main Results and Contributions to Literature

The focus of chapter two is analyzing the impact of regulation (Basel III in particular) on crisis probability. We sample our data to capture the period of regulation. The results show Basel III leverage ratio behaves inversely to crisis probability while traditional bank leverage (debt to equity ratio) has a positive relationship. Reflecting the change in how leverage ratio is calculated in Basel III that shows regulators have taken into consideration the impact of non-balance items that are said to be instrumental in the crisis (e.g. CDS). Comparing Basel III coefficients between our samples, the regressions shows a clear improvement in the regulatory variables probabilities to reduce crisis. The result show a change in; capital adequacy ratio, bank liquidity ratio and bank leverage ratio affecting the crisis dependent variable from 2.4%, 1.5%, and 5.7% to 7.01%, 5.2% and 9.7% respectively after regulation. The results show an improvement over related literature that calibrated the data to understand this impact, e.g. Barrell et al. (2010a). The BMA results shows that the estimates from Basel III thresholds are robust. Our analysis suggests the introduction of these Basel III variables to the EWS literature for future analysis.

Furthermore, our result show an inverse relationship between real economic growth and probability of crisis occurring and a positive relationship between growth in house prices and crisis probability. The analysis shows that at a 10% level of significance, interest rate is significant in explaining the crisis, similar to the work of Demirgüç-Kunt and Detragiache (2005).

Chapter 3 analysed the impact of regulation to systemic risk. Our results present important findings about regulation implemented after the crisis period in the UK. The main one being ring fencing. Using interest income as a proxy for this regulation, our analysis show that this variable has no statistical significance in reducing systemic risk after regulation. This is further supported when we look at the result of our non-interest income (a proxy for non-ring fence activities) that was expected to increase systemic risk but showed no such relationship in the post-regulatory period. Similar conclusion was reached by De Jonghe et al. (2015). Therefore important for policy makers to consider the implications of this policy. Our result show that measures taken to reduce bank size to be of statistical significance with an inverse relationship systemic risk. This is in line with results from Laeven et al. (2016), that find strong evidence that systemic risk increases with bank size. Allowing us to conclude that the effort by regulatory agency to reduce bank size is effective.

Finally, our results show that Basel III variables provide strong and valid justification in the attempts made by regulation to reduce systemic risk. It shows that more capitalised banks are better able to reduce systemic risk and the new leverage ratio also reduces systemic risk. This is similar with the results of Berger and Bouwman (2013) who show that bank capital increases a bank's survival probability, showing that the increase in capital regulations reduces the exposure of banks to systemic risk.

Our main contribution to the literature is analysing the impact of regulation using our systemic risk measure (ΔCoVaR) against bank level targeted variables. Our second contribution relates to the analysis of systemic risk. Previous literatures (e.g. Girardi and Ergün, 2013, Huang et al., 2012a, Tobias and Brunnermeier, 2016) have used both models (i.e. CoVaR and Garch) applied here when estimating systemic risk. However, what we have added is the application of accuracy tests to show the model that is more accurate when estimating systemic risk (on bank regulatory variables). This study considers variables that were either newly introduced (such as ring fencing) or those that are calculated differently (e.g. leverage ratio, regulatory capital) because of changes in the regulation. Therefore, providing a clear understanding of the impact these policies have created on systemic risk.

Chapter four studies the effects of contagion at sector level within the whole economy. We use data from CDS indexes to examine whether contagion occurred across various sectors and if the introduction of regulation resulted in changing this relationship to interdependence. Our results from the Markov switching VAR specification reveal the existence of two Regimes in our data and that there was contagion effects among these CDS indexes that changed to interdependence due to the introduction of regulation. Guo et al. (2011) also confirmed the existence of contagion between stock market, real estate market, credit default market, and energy market.

This chapter's first and main contribution is analysing the impact regulation has had on credit default swap indexes in reducing the contagion. The second contribution of this analysis establishes if there was contagion or interdependency within sectors of the economy in the US and the UK during the crisis and if this has changed after introducing regulation. The third contribution shows through which channel contagion occurred. That is, which CDS index contributed to propagation of risk within the economy through the application of Impulse Response Functions (IRF's).

A number of striking findings emerge from the study. Firstly, we find the use of CDS was economy wide, i.e. most of the sectors in the economy were heavily involved in the use of CDS instruments. The results show that in the US the sectors that were most affected by contagion effects are Telecomms and Transportation, with Banks and Other Financial Services experiencing lesser contagion impact (this is contrary to the general assumption). While in the UK, most affected sectors were Banks, Manufacturing and then Other Financial Services. Our findings have important implications for policymakers regarding the amplified contagion effects among the sectors during financial crisis, to avoid lack of oversight. In particular, they should monitor the use of CDS from the sectors that displayed most impact of contagion.

5.1.1 Concluding Remarks, Policy Implications and Further Research

The precise understanding of how variables reacted to changes in regulation goes beyond calibrating data (as necessary done before implementing policy changes) to sampling empirical data in a manner that capture breaks and models that are more accurate in showing these stylized impacts. This thesis addressed gaps found in prior research. We addressed the changed in relationship between crisis phenomena and variables identified to contribute to crisis and therefore subject to recent regulatory changes. From theoretical arguments of economics regulation, we explored the importance of banking sector and its regulation. We looked at the rationale provided for the various variables targeted by regulatory changes. We highlighted the difference in regulatory changes implemented in the UK and US (being the most impacted countries by the crisis). Most importantly, we analysed the impact of regulation after the crisis. We analysed the probability of crisis, systemic risk, contagion and its channels of spread.

The literature in this area has been focused on variables that caused the crisis, while the focus in our analysis looks at the variables that regulation either changed or introduced. By dividing our samples, we were able to highlight how variables behaved before the crisis, and most important how regulation has impacted on them to make the system more resilient afterwards. We have showed how the implementation of regulation has reduce the probability of another crisis happening, reduced systemic risk and changed the effects of contagion to interdependence. We have also shown the channels through which systemic risk flowed via CDS within different economic sectors. Our analysis has also shown how some of the individual national regulatory measures are not supported by our statistical analysis.

Part of the implication of this study to policy makers relates to understanding the impact regulation is having, therefore providing a basis for future policy trajectory. We have highlighted already that regulation is not costless. Therefore, this study sheds light on some variables that have not to impact on crisis, therefore recommends further policy reconsideration. Most importantly, the study has shown clearly the extent that regulation has impacted the various aspects of the crisis, i.e. crisis probability, systemic risk and contagion, and reached the conclusion that regulation is making the whole system more resilient. Our findings also suggests policymakers to monitor sector CDS effects to avoid oversight. In particular, they should monitor the use of CDS from the sectors that displayed most impact of contagion.

Again, our data sets have shown models that are more accurate in measuring the different concepts of crisis analysed here. Therefore shedding more light in terms of academic discourse. Our analysis have also identified variables to were not previously part of the early warning signal literature and recommend the inclusion of these as supported by statistical results and use within regulatory changes. The analysis also identified channels through which contagion flows within CDS market, the variables that were most affected by systemic risk and how regulation has made them and the system more resilient to crisis. Therefore useful for market participants to better understand risk from a regulatory and systemic point that can aid in the process of decision making within firms.

Finally, this study acknowledges some areas of limitation that future studies should consider. Our analysis focused on impact of regulation in relation to crisis risk. However, we highlighted already that regulation is not costless. Therefore, a cost/benefit analysis of regulation after the crisis will certainly present a more holistic understanding on the impact of regulation after the crisis. As Barrell et al. (2009) stated that regulation can be seen as a tax to the banking system, with cost not only limited to the banks but can spill over to the economy at large via cost of borrowing to household and business that can lead to reduction in output.

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