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Essays on Financial Stability

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Declaration of Authorship

I, Mohamed Bakoush, declare that this thesis titled, “Essays on Financial Stability” and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.
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- Bakoush, M., Gerding, E. and Wolfe, S., 2016. Modelling the Dynamics of Systemic Risk in Over-The-Counter Interest Rate Derivatives Market. Computing in Finance and Economics Conference. June 2016. Bordeaux, France.
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Signed:

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"It's all about risk!"

University of Southampton

Abstract

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Essays on Financial Stability

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The thesis analyses dynamics of systemic risk and contagion in securitization, interbank and derivatives markets, and the subsequent implications for financial stability and macroprudential policy. In doing so, three distinctive lines of research are pursued. First, we examine the impact of securitization on bank stability and systemic risk. Following this, we analyse distress spillover from the OTC derivatives market into the interbank market, due to the interaction between margin procyclicality in OTC derivatives markets, and funding liquidity risk in the interbank market. Finally, we develop a macroprudential stress test, that explicitly links liquidity risk and solvency risk of banks, as well as account for interconnectedness among them.

We provide evidence that securitization activities are destabilizing at both the individual bank level and the banking system level, and tend to increase commonality of asset returns among banks leading to increased interconnectedness and systemic risk. Moreover, we show that distress due to margin procyclicality in the OTC derivatives market can spillover to the interbank market leading to episodes of systemic liquidity risk. We also show that central clearing might increase the possibility of systemic liquidity risk due to tight margin requirements and the timing of cash flows required from banks. Further, using the proposed stress test, we effectively identify the systemic vulnerability of individual banks and the resilience of the banking system as a whole to economic shocks.

The results of this thesis have far-reaching policy implications. First, given the current increasing pace in monetary policy tightening, our findings on the destabilizing effect of securitization activities are of great interest to policy makers in their attempts to revive securitization markets, as they provide a framework for regulators to think about the effects of securitization at both the bank level and the banking system level. Moreover, our findings on the negative consequences of margin requirements should inform regulators about the the importance of striking the balance between limiting counterparty credit risk through tight margin requirements, and the side effect of increasing the possibility and magnitude of systemic liquidity crises. Finally, the proposed stress test provides an effective tool for the banking system supervisors to analyse the current state of the system stability and to monitor the evolution of contagion and systemic risk within the system.

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To my family, and the Egyptian people.

Chapter 1

Introduction

1.1 Preamble

This thesis aims to provide new insights into financial stability and macroprudential policy. To this end, this thesis provides three distinctive analyses that focus on the dynamics of contagion and systemic risk in the securitisation, derivatives, and interbank markets, which were in the midst of the global financial crisis of 2008. In doing so, this thesis applies the theory of complex systems to evaluate different channels of contagion in the financial economy including balance sheets commonality, interbank connectedness, and capital market volatility; and to analyse the systemic aspects and interactions between liquidity risk, funding risk, and solvency risk.

1.2 Research Context

The main inquiry in this thesis stems from the global financial crisis of 2008 and its ongoing ramifications. This crisis has reshaped the recent economic history in different ways. The starting point of the crisis might have been the loosening of monetary policy in the aftermath of the Dot-com bubble, which led banks to expand mortgage lending including subprime mortgages. By 2007, a bubble in the housing market has already been formed. The bursting of this bubble has led to devastating effects on both the financial and real economy, and caused what has become known as the Great Recession, the most severe economic recession since the Great Depression of 1929. However, the severity of the Great Recession can not be fully attributed to the initial housing bubble. In fact, this severity was due primarily to the panic in funding and securitisation markets, which disrupted the supply of credit (Bernanke, 2018).

The financial crisis has highlighted the fact that the financial economy is a complex system. Indeed, one of the main contributing factors to the devastating effects of the financial crisis has been interconnectedness that originated in financial markets in the run-up to the crisis (Yellen, 2013). Mortgage lenders relied heavily on short-term funding sources from the interbank market to fund their lending. This created an indirect link between the housing and interbank markets, and meant that sudden stops in any of them will be transferred to the other. Mortgages in turn found their way to capital markets through mortgage credit securitisation (e.g. collateralised debt obligations); and to the over-the-counter derivatives markets through mortgage credit derivatives (e.g. credit default swaps on mortgage securities). This led interconnectedness among the housing, banking, and capital markets to increase in an unprecedented way. Interconnectedness has also increased within the banking system where banks acted as lenders and borrowers to each other in the interbank market, counterparties to each other in the derivatives markets, and issuers of or investors in securitised assets of each other. Subsequently, the contagion that was triggered by losses in mortgages and declines in the prices of mortgage-backed securities has spread through the interbank channel and translated into liquidity hoarding and funding dry-ups, which led to bankruptcies and decline in the credit supply to the real economy. Contagion has also spread through balance sheets of financial institutions leading to further declines in asset prices and fire sales. In short, the increased complexity of the financial system in the run-up to the crisis, and the panic in securitisation and funding markets have paved the way for the unprecedented systemic crisis of 2008.

The financial crisis has also highlighted serious limitation at both the economic analysis and economic policy frontiers. Traditional economic models use representative agents to study the behaviour of individual economic actors such as households and firms, where agents make decisions to maximise their own utility based on their expectations regarding macroeconomic outcomes. An important caveat of this class of models is that the financial sector is often represented by a single representative agent that simply provides funding to the wider macroeconomy (Blanchard, 2009). In addition, they generally focus on the business cycle and ignore the role of the financial cycle in macroeconomics (Borio, 2014), in contrast to previous views on the importance of the financial cycle in determining financial stability (Minsky, 1977, 1982). Although these models have had some success at traditional monetary policy analysis, needless to say, they have failed to predict or even explain the causes or the scale of the financial crisis.

At the policy frontier, regulations treated financial institutions individually and have not accounted for the implications of interactions between them. The focus of regulations such as Basel II accords was to keep individual banks solvent through adequate capital requirements in order to ensure the stability of the financial system as a whole. Despite the earlier views of some top policy makers that this is a fallacy of composition (Crockett, 2000), the regulatory approach remained predominantly microprudential in the run-up to the crisis. Moreover, the financial crisis has emphasised that the financial system is mainly characterised by the connections and interactions between its participants. In response to shocks to the system, financial institutions may change their preferences and may engage in herding behaviour in the face of uncertainty. This renders microprudentially oriented financial regulations prone to the paradox of prudence (Brunnermeier and Sannikov, 2016), whereby in stress time, seemingly rational decisions by individual financial institutions can have negative externalities on the system as a whole, which might lead to the emergence of systemic risk not captured in traditional economic models.

Thus, there remains a need for a class of dynamic models that can capture non-linear second and subsequent round effects of systemic risk that result from connections and interactions between financial agents in financial markets; and can work effectively to inform regulatory policy actions during crisis times. One approach to achieve this ambitious objective is using tools of the complex systems theory to study the topology of financial markets and how micro interactions between agents can drive macro behaviour. It is becoming increasingly common to view financial systems as networks of interlinked institutions, whose multiple interconnections make them robust, yet fragile (Haldane and May, 2011). In fact, the roots of complex systems theory in economics can be traced back to the work of Friedrich Hayek (Hayek, 1964) and Herbert Simon (Simon, 1962) on complexity. Models in this paradigm appear promising to understanding dynamics of contagion and systemic risk in a variety of financial systems. They focus on perturbing the system with an external shock in order to understand the contagion dynamics on the network, with the aim of calibrating regulations and necessary measures to prevent systemic failures (Gai et al., 2011).

1.3 Thesis Overview

This thesis applies techniques from complex systems theory to study dynamics of contagion and systemic risk in financial markets. One of the main techniques applied here is agent-based modelling which has lent itself to various applications in the field of financial economics to investigate vulnerabilities and threats to financial stability (Bookstaber, 2012). These models are rooted in the work of Herbert Simon on bounded rationality, which represents the basis for most of the recent behavioural economics discipline (Simon, 1982). Building on Simon's work, agent-based models focus on modelling the dynamic interactions among agents of several types, where behaviour is not always microfounded by optimising expected utility and markets are not always in equilibrium. In the same vein, this thesis utilises agent-based models in Chapter 3 in an attempt to model some of the vulnerabilities in the financial economy without having to abstract away inherited features of this economy such as heterogeneity of financial institutions, the effect of financial institutions' interactions on their environment, and the fact that financial institutions are adaptive to one another's actions. Indeed, recent advancements in the application of these models in the fields of finance and economics have shown their ability to simulate the real economy and financial markets to explore quantitatively how they are likely to react under different scenarios (Farmer and Foley, 2009). Therefore, the model presented in Chapter 3 of this thesis represents participants in over-the-counter derivatives and interbank markets as agents that interact and may adapt to new outcomes, that use their knowledge about their counterparties to form rules of interactions, and whose decisions are basically based on real-world bounded rationality.

Furthermore, this thesis utilises network theory as a natural tool for understanding complex interactions within financial markets such as the over-the-counter derivatives and interbank markets. This approach to studying financial markets provides better understanding of the interconnectedness and the propagation of systemic risk within these markets (Summer, 2013). Simple network structures have been utilised in early research to study how systemic risk arises through liquidity shocks that can have a domino effect (Allen and Gale, 2000); how interbank credit extensions to cover deposits can result in institutions that are too interconnected to fail (Freixas et al., 2000), and how the lack of information can create systemic risk in financial networks (Caballero and Simsek, 2013). Not surprisingly, interest in this technique has increased considerably since the financial crisis. In fact, recent models have shown the ability of more real, albeit complex, network structures to provide better measurement of systemic risk and financial instabilities (e.g. Gai et al., 2011; Gai and Kapadia, 2010; Glasserman and Young, 2015, 2016; Elliott et al., 2014; Acemoglu et al., 2015). In the same vein, this thesis utilises network techniques in Chapters 3 and 4 in order to depict the relationships and connections between financial institutions in the over-the-counter derivatives and interbank markets. Further, the network developed in

Chapter 3 is a multilayer network, which is used to fully capture the interconnectedness between institutions in both markets. In these networks, financial institutions represent the nodes and financial contracts and exposures represent the edges between these nodes.

1.4 Thesis Contributions

This thesis is structured along three public policy debates in financial stability. The thesis analyses dynamics of systemic risk and contagion in securitisation, interbank and derivatives markets, and the subsequent implications for financial stability and macroprudential policy. One chapter is devoted to each one of the three different lines of research. The connecting theme of these chapters is their ultimate focus on financial stability. A brief summary of the contributions of each chapter is provided below.

1.4.1 Contributions of Chapter 2

Chapter 2 titled "Securitisation, Monetary Policy, and Bank Stability" sets the scene in the thesis.[1] It looks back at securitisation activities with a more critical lens to analyse their role in bank stability and systemic risk in the run-up to the global financial crisis. Following a detailed review of the vast body of literature on the impact of securitisation on bank performance and stability, this chapter evaluates whether securitisation activities have impaired bank stability and contributed to the onset of the systemic crisis of 2008. To this end, this chapter examines how securitisation affects both bank profitability and risk and how these effects in turn determine the net impact of securitisation on bank stability and further on systemic risk at the banking system level. While previous research in this area focuses on the effects of securitisation on different aspects of

[1] Parts of this chapter has been published as: Bakoush, M., Abouarab, R. and Wolfe, S., 2018. Disentangling the Impact of Securitisation on Bank Profitability. *Research in International Business and Finance*. **47**: 519-537.

bank performance separately, this chapter develops a framework that combines insights from the line of research that focuses on the effects of securitisation on bank performance and the line of research that focuses on the channels through which securitisation affects bank performance.

In particular, Chapter 2 develops a structural model of bank performance that combines profitability and risk, as well as considers the main channels through which securitisation affects bank performance, namely liquidity and cost of funding. This model is further developed to study the effects of securitisation on bank stability. Based on this framework, Chapter 2 proposes a new index (*S–score*) that measures the net impact of securitisation activities on bank stability and the stability of the banking system as a whole. This measure is estimated at both the loan portfolio level and the overall balance sheet level. The results show that securitisation activities tend to boost both profitability and risk of banks that engage in these activities, creating a trade-off in bank performance. Further, analysis of the dynamics of the *S–score* measure at both the individual bank level and the banking system level shows that securitisation activities have a destabilising effect on securitiser banks. Securitisation also tends to increase commonality of asset returns among banks leading to increased interconnectedness and systemic risk.

At the policy frontier, Chapter 2 evaluates the role of monetary policy in determining the net effect of securitisation on bank stability. The results of this analysis show that low monetary policy short-term interest rates in the aftermath of the global financial crisis have mitigated the destabilising effect of securitisation on banks. These findings are of great interest to policy makers in their attempts to revive securitisation markets to boost banking efficiency and risk sharing in capital markets. Chapter 2 provides a framework for regulators to think about the effects of securitisation at the bank level and the banking system level. It is important that regulators consider the effects of securitisation on a risk-adjusted performance basis, and to consider the different channels through which securitisation affects bank stability.

1.4.2 Contributions of Chapter 3

Chapter 3 titled "Margin Requirements and Systemic Liquidity Risk", *forthcoming in the Journal of International Financial Markets, Institutions and Money*, adds a new dimension to the analysis of systemic risk and contagion in financial markets.[2] On the one hand, the chapter analyses the spillover of distress from over-the-counter derivatives markets into the interbank market. In doing so, it considers the interaction between margin procyclicality in OTC derivatives markets, and funding liquidity risk in the interbank market. On the other hand, Chapter 3 utilises an innovative combination between two prominent techniques from the theory of complex systems, namely agent-based modelling and network analytics. In this chapter, agent-based modelling is used to capture the heterogeneity and interactions among participants in both the OTC derivatives market and the interbank market, whereas networks is used to depict the interconnectedness among participants in these markets.

In particular, Chapter 3 develops a model in which margin procyclicality in OTC derivatives markets and the propensity for liquidity hoarding in the interbank market interact to generate a systemic liquidity crisis. In this model, banks lend and borrow in the interbank market to mitigate liquidity risk and trade derivatives contracts in the OTC derivatives market to mitigate market risk. The daily mark-to-market of derivatives contracts results in daily margin calls that

[2] In addition, a version of the model presented in this chapter has been used to study the impact of the market turmoil, that followed the Brexit vote in June 2016 in the UK, on margin calls for banks. The results of this analysis have been reported in a separate paper currently under review for publication in *Finance Research Letters*: Bakoush, M., Gerding, E. and Wolfe, S., 2017. Interest Rate Swaps Clearing and Systemic Risk.

banks cover using high quality liquid assets. The model shows that distress due to margin procyclicality in the derivatives market can spillover to the interbank market leading to episodes of systemic liquidity risk. Interconnectedness further amplifies the effects of systemic risk within the interbank market. The model also shows that central clearing might increase the possibility of systemic liquidity risk due to tight margin requirements and the timing of cash flows required from banks. Results also show that haircut levels affect the possibility of systemic liquidity risk, and highlight the potential role of a market maker of last resort in limiting this possibility.

At the policy frontier, Chapter 3 provides several insights into macroprudential policy making. This chapter considers one of the overlooked side effects of margin requirement regulations that were enacted in the aftermath of the global financial crisis. It also highlights that central clearing might in fact contribute to increasing funding liquidity risk in its attempt to reduce counterparty credit risk. The findings of this chapter suggest that regulators should take measures to strike the balance between reducing counterparty credit risk and inducing the onset of a systemic liquidity crisis. This chapter, thus, provides the first attempt to analyse the side effects of margin requirements on systemic liquidity risk, by highlighting the implications of these margin requirements for funding liquidity risk in the interbank market.

1.4.3 Contributions of Chapter 4

Chapter 4 titled "Macroprudential Stress Testing of Bank Liquidity and Solvency" makes further contributions to the literature on systemic risk and financial stability. This chapter develops an innovative framework for a macroprudential stress test of banks, that addresses some of the limitations of the current practice of macroprudential stress testing. First, the stress test presented in this chapter considers the interactions between liquidity risk and solvency risk of banks. Second, this stress test takes a systemic view of the banking system and accounts for interconnectedness among banks and possibilities of systemic risk propagation within the banking system. To the best of the author's knowledge, both factors have not previously been considered together in current practice of macroprudential stress testing.

In particular, Chapter 4 develops a macroprudential stress test which explicitly links liquidity risk and solvency risk in order to incorporate their interactions in the stress testing framework. This link is created by estimating both the probability of a bank becoming illiquid and the probability of becoming insolvent based on the same factor, namely systemic distress. To this end, Chapter 4 proposes a new measure of systemic distress called *DistressRank* which is based on the notion that the distress level of a bank is a function of its idiosyncratic risk as well as its systemic risk stemming from being connected to counterparties through interbank assets or liabilities. Thus, *DistressRank* fully captures the interbank network topology and provides an innovative way to incorporate interconnectedness between banks into the stress test design. Further, the stress test framework relies on two sets of stress scenarios, where the first is designed to assess the resilience of the banking system to macroeconomic shocks, and the second is designed to assess the possibility of amplifying endogenous shocks within the banking system and transmitting them to the macroeconomy.

At the policy frontier, Chapter 4 presents various insights for macroprudential policy making. First, the proposed stress test can be used to effectively identify the systemic vulnerability of individual banks and the resilience of the system as a whole to economic risks. Second, it can also be effective for monitoring and assessing systemic interdependencies among banks. Thus, the proposed stress test provides an effective tool for the banking system supervisors to analyse the current state of the system stability and to monitor the evolution of contagion and systemic risk within the system.

1.5 Thesis Structure

The remainder of this thesis is made up of four chapters:

- **Chapter 2** provides a model to evaluate the impact of securitisation activities on bank stability and systemic risk, along with an analysis of the role of monetary policy in determining this impact.

- **Chapter 3** provides a model to study the spillover of distress from over-the-counter derivatives markets into the interbank markets, with a focus on the interaction between margin procyclicality and liquidity hoarding.

- **Chapter 4** provides a framework for a macroprudential stress test of banks that considers the interactions between liquidity risk and solvency risk, and considers the interconnectedness in the banking system network.

- **Chapter 5** provides an overall summary of the contributions of this thesis, along with the most important policy implications arising from the thesis findings. It also provides a critical assessment of the methods and techniques employed in this thesis. Finally, avenues for future research are identified, and a concluding remark is provided.

Chapter 2

Securitisation, Monetary Policy and Bank Stability

Chapter 2: Securitisation, Monetary Policy and Bank Stability[1]

Abstract

We study the effects of securitisation on bank performance and stability. We examine how securitisation affects both bank profitability and risk and how these effects in turn determine the net impact of securitisation on bank stability and further on systemic risk at the banking system level. We find that securitisation activities tend to boost both profitability and risk of banks that engage in these activities, creating a trade-off in bank performance. Further, we propose *S–score* as a measure of the net effect of securitisation activities on bank stability. Analysis of the dynamics of this measure at the individual banks level and the banking system level show that securitisation activities have a destabilising effect on securitiser banks. Securitisation also tend to increase commonality of asset returns among banks leading to increased interconnectedness and systemic risk. We also find that low monetary policy short-term interest rates in the aftermath of the global financial crisis have mitigated the destabilising effect of securitisation on banks.

Keywords: Securitisation; Bank Profitability; Bank Risk; Bank Stability; Systemic Risk; Monetary Policy

JEL Classification: G10; G21

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[1]Research output based on this chapter include:
Bakoush, M., Abouarab, R. and Wolfe, S., 2018. Disentangling the Impact of Securitization on Bank Profitability. *Research in International Business and Finance*. **47**: 519-537.
Bakoush, M., and Wolfe, S., 2018. Securitisation, Monetary Policy and Bank Stability. *Working Paper.*

2.1 Introduction

Securitisation has fundamentally altered the way in which financial intermediation is organised as it has provided banks with an innovative way to improve efficiency and performance. Banks may be incentivised to use securitisation in order to improve their cost of funding (Pennacchi, 1988), to improve their risk management (Cebenoyan and Strahan, 2004), or to improve their profitability (Affinito and Tagliaferri, 2010). However, these benefits for individual banks remain largely theoretical given that empirical evidence does not uniformly support them. Further, securitisation was blamed for increasing systemic risk and being a primary cause of the 2008 US mortgage crisis where it acted as the vehicle for the increase in lower-quality subprime debt.

This chapter contributes to three different strands of academic research. The first strand aims to understand the effects of securitisation on bank performance and stability. In particular, this chapter examines how securitisation affects both bank profitability and risk and how these effects in turn determine the net impact of securitisation on bank stability. The second strand is related to the effect of securitisation on systemic risk at the banking system level. This chapter examines the commonality among the returns from securitisation activities of banks as an indicator of systemic risk in the banking system. The third strand of research is related to the relationship between securitisation and monetary policy. In particular, this chapter examines whether the low interest rates in the aftermath of the global financial crisis have improved or worsened the effects of securitisation. That said, our analysis differentiates between the period that preceded and the period that succeeded the global financial crisis of 2008 in order to account for the structural differences in both the banking industry and securitisation markets.

We first analyse the relationship between profitability and risk of banks that engage in securitisation activities compared to non securitiser banks. Given the dependency in bank profitability and simultaneity between profitability and risk, we use a dynamic panel data model to adjust for these issues. We estimate this model using the dynamic system generalised method of moments (System-GMM) estimation method which accounts for simultaneity, unobserved heterogeneity, and dynamic endogeneity in dynamic panel data models. The results suggest a trade-off between profitability and risk for banks that engage in securitisation activities compared to non securitiser banks. In other words, for a securitiser bank to increase its profitability, it needs to bear more risks.

We then analyse whether securitisation activities can explain this trade-off between profitability and risk. In so doing, we develop a framework that combines insights from the strand of research that focuses on the effects of securitisation on bank performance (e.g. Casu et al., 2011, 2013) and the strand of research that focuses on the channels through which securitisation affects bank performance (e.g. Loutskina and Strahan, 2009; Loutskina, 2011). In particular, we develop a structural model of bank performance as a function of securitisation activities, that consists of a system of simultaneous equations. This approach enables us to simultaneously consider the effects of securitisation on both profitability and risk, while accounting for the two main channels through which securitisation affects profitability and risk, namely liquidity and cost of funding.

The results show that securitisation can explain why profitability and risk of securitiser banks tend to increase together. On the one hand, securitisation improves banks profitability by allowing banks to sell less liquid loans and use the generated funds to grant new loans, hence, increasing fee-based revenues. On the other hand, the increase in profitability comes at the expense of increasing bank risk as banks expand their risk taking securitisation activities given their ability to securitise loans and shift associated risk to capital markets.

Further, we propose a new index to measure the impact of securitisation on bank stability (*S–score*) that effectively captures banks' net exposure to securitisation activities. To construct this index, we adjust our structural model of the bank performance to account for risk-adjusted profitability as a function of securitisation activities, instead of considering profitability and risk separately. As a result, the *S–score* can be thought of as a measure of the sensitivity of the bank risk-adjusted profitability to its engagement in securitisation activities, where the sensitivities are estimated based on a structural model of bank stability that accounts for the main channels through which securitisation affects bank risk-adjusted profitability. We estimate *S–score* at the loan portfolio level and the overall balance sheet level, for both individual banks and the banking system as a whole.

The results show that securitisation activities are destabilising at the bank level. The net impact of securitisation on banks is generally negative when we measure bank performance based on risk-adjusted profitability measures. This impact is negative whether at the loan portfolio level or the overall balance sheet level. This destabilising effect is more significant in the period that led to the global financial crisis in 2008 compared to the period that followed the crisis. In addition, the dynamics of *S–score* at the banking system level show that the destabilising impact of securitisation is more severe in the run-up to the global financial crisis, whereas it bottoms out during the crisis. Following the crisis, the destabilising effect seems to have declined. Nevertheless, neither our estimate of *S–score* at the loan portfolio level nor at the balance sheet level show any significant positive effects of securitisation on bank stability, even in the aftermath of the global financial crisis.

We further extend our analysis to evaluate the systemic effects of securitisation at the banking system level. To this end, we implement the principal components analysis approach suggested by (Billio et al., 2012) to measure the commonality among returns from securitisation activities of banks as an indicator of the systemic effects of securitisation activities. It is expected that the first few components will capture a larger portion of the total volatility when returns tend to move together, which is often associated with crisis periods. Therefore, we analyse the systemic effects of securitisation by examining the portion of volatility in returns from securitisation activities that is explained by the first few principal components. An increase in this portion is indicative of increased commonality in returns from securitisation activities and increased interconnectedness among banks, and accordingly higher systemic risk.

The results suggest that the first principal component was increasing in the run-up to the global financial crisis, and then peaked exactly at the end of 2008. On average, the first principal component explains a much higher portion of the volatility in returns from securitisation activities in the period that preceded the global financial crisis compared to the period that followed the crisis. This implies that securitisation activities have contributed to increasing interconnectedness among banks in the run-up to the global financial crisis, hence increasing systemic risk in the banking system.

An interesting finding throughout our analysis is that the effects of securitisation on either profitability, risk, stability, or systemic risk differ significantly between the period that preceded and the period that succeeded the global financial crisis of 2008. We put forward an explanation for this difference. We argue that the severe decline in monetary policy short-term interest rates might have affected bank incentives to securitise loans and has mitigated the destabilising impact of securitisation on banks following the onset of the crisis. We put this argument to the test using an identification strategy centred around the exogenous monetary policy shock that coincided with the crisis. In particular, to analyse how the net impact of securitisation activities depends on monetary policy interest rates, we employ a difference-in-differences (DID) approach in which we compare the *S–score* of banks before and after the decline in monetary policy rates following the crisis. In other words, we evaluate whether the destabilising impact of securitisation has changed around the dramatic decline in short-term interest rates following the crisis. We estimate this difference-in-differences model using a balanced window of eight years of data surrounding the fourth quarter of 2008.

The results show that *S–score*, either measured at loan portfolio level or the balance sheet level, has improved in the low interest rate period compared to the higher interest rate period. Nevertheless, the magnitude of improvement in the destabilising effect of securitisation is higher when measured at the loan portfolio level compared to being measured at the balance sheet level. In addition, the magnitude of this improvement is supported by our previous estimates of *S–score* at the banking system level. Overall, the results support the mitigating role of low interest rates on the net impact of securitisation on bank stability as measured by *S–score*.

Finally, given that in response to the global financial crisis, several regulatory initiatives were enacted, the effect of monetary policy interest rates could be commingled with the effects of other policy initiatives that coincided with monetary policy decline following the crisis.[2] Therefore, to check the robustness of our results from the difference-in-differences analysis, we conduct an additional test in which we examine the impact of monetary policy interest rates on the return

[2] Examples include the Housing and Economic Recovery Act of 2008, and the Dodd-Frank Act of 2010.

and riskiness of securitisation activities. This approach has the added benefit of explicitly considering the direct impact of monetary policy interest rates on the profitability and riskiness of securitisation activities, which translates into effects on bank stability.

The results support the view that the decline in monetary policy rates in the period that followed the crisis has contributed to mitigating the destabilising impact of securitisation. On the one hand, our results show that changes in short-term interest rates have positively affected both profitability and riskiness of securitisation activities in the run-up to and the period that followed the crisis. On the other hand, the results show that the magnitude of this impact declines significantly in the period that followed the crisis, with a more dramatic decline in the case of riskiness of securitisation activities. Put together, these findings lead us to conclude that the decline in monetary policy interest rates have worked to mitigate the destabilising impact of securitisation in the aftermath of the crisis.

This chapter contributes to the strand of literature that explores the impact of securitisation on bank performance. Securitisation enables banks to convert illiquid assets quickly into cash and to remove liabilities associated with these assets from their balance sheets. The cash proceeds from securitisation can be used in different ways. For example, it can be used to replace existing funding sources such as deposits, consequently, reducing interest expense accrued for these deposits, and leading to higher reported earnings (Marques-Ibanez and Scheicher, 2012). Additionally, banks can use these proceeds to grant new loans that can be securitised later, thus repeating the same process and creating an asset-securitisation pipeline structure (Wolfe, 2000). This structure allows banks to receive fee income for servicing the securitised loans, and to improve their return on equity effectively because the new income can be supported by a smaller equity base (Kopff and Lent, 1990). Moreover, proceeds from securitisations can be reinvested in loans directed to new profitable projects, thus aligning the average rate of the bank's loan portfolio with the market rate and increasing the bank's income from interest (Thomas, 1999). These views on the positive impact of securtitisation are also supported by some empirical studies. While Greenbaum and Thakor (1987) suggest that securitisation allows banks to specialise in activities of comparative advantage and to shifting the activities of comparative disadvantage, Boot and Thakor (1993) show that in the presence of asymmetric information, securitisation of assets enables the issuer to increase its expected revenue. Nevertheless, studies on the U.S. banks are not conclusive. Jiangli et al. (2008) show that U.S. banks would have been more profitable without securitisation activites, whereas Casu et al. (2013) compare between securitisers and non-securitisers based on different performance indicators, and find that profitability is significantly and positively affected by securitisation.

This chapter also contributes to the line of research on the impact of securitisation on bank risk. Instefjord (2005) suggests that this impact is twofold. On the one hand, it may reduce bank risk by shifting credit risk to the market and improving risk sharing opportunities. In support of this view, Cebenoyan and Strahan (2004) argue that aggressive use of securitisation encourages banks to take more risk; however, the new risk is still outweighed by the credit risk initially transferred to investors. Jiangli et al. (2008) show that securitisation reduces insolvency risk. They provide evidence that, during the 2007-2009 credit crisis, mortgage credit and securitisation markets disorders were due to excess supply in those markets. Affinito and Tagliaferri (2010) show that banks tend to keep high-quality loans while securitising their worst loans. Similarly, some studies demonstrate that in the run up to the credit crisis, US banks managed to securitise their worst mortgage loans, thus reducing credit risk (see Mian and Sufi, 2009). On the other hand, securitisation may increase bank risk due to the increase in risk taking and recourse or other seller-provided credit enhancements

(Higgins and Mason, 2004). Ambrose et al. (2005) suggest a positive effect of securitisation on bank credit risk due to retaining riskier loans while selling safer ones in response to regulatory requirements. Calomiris and Mason (2004) and Casu et al. (2011) show that high amounts of outstanding securitisations reduced U.S. banks risk appetite prior to the financial crisis. They attribute this to the recourse hypothesis implying an already high credit risk. Moreover, Bedendo and Bruno (2012) provide evidence that U.S. banks intensively used securitisation to obtain funds, in times of frozen liquidity markets during the financial crises, at the expense of higher overall bank risk. Similar evidence is provided for European banks in Uhde and Michalak (2010) and for Italian banks in Battaglia and Gallo (2013).

The remainder of this chapter is organised as follows. Section 2.2 provides an institutional background and an overview of the data sample. Section 2.3 analyses the relationship between profitability and risk of securitisers. Section 2.4 explains the trade-off in bank performance using securitisation activities. Section 2.5 analyses the impact of securitisation on bank stability and systemic risk. Section 2.6 evaluates the role of monetary policy in determining the effects of securitisation. Section 2.7 concludes the chapter.

2.2 Background and Data

This section provides an overview of the US banking industry and securitisation market, in addition to the data sample and variables used throughout the analysis in subsequent sections.

2.2.1 Institutional Background

The US banking industry has experienced an enormous transformation over the course of the last few decades. One of these transformations was a trend of

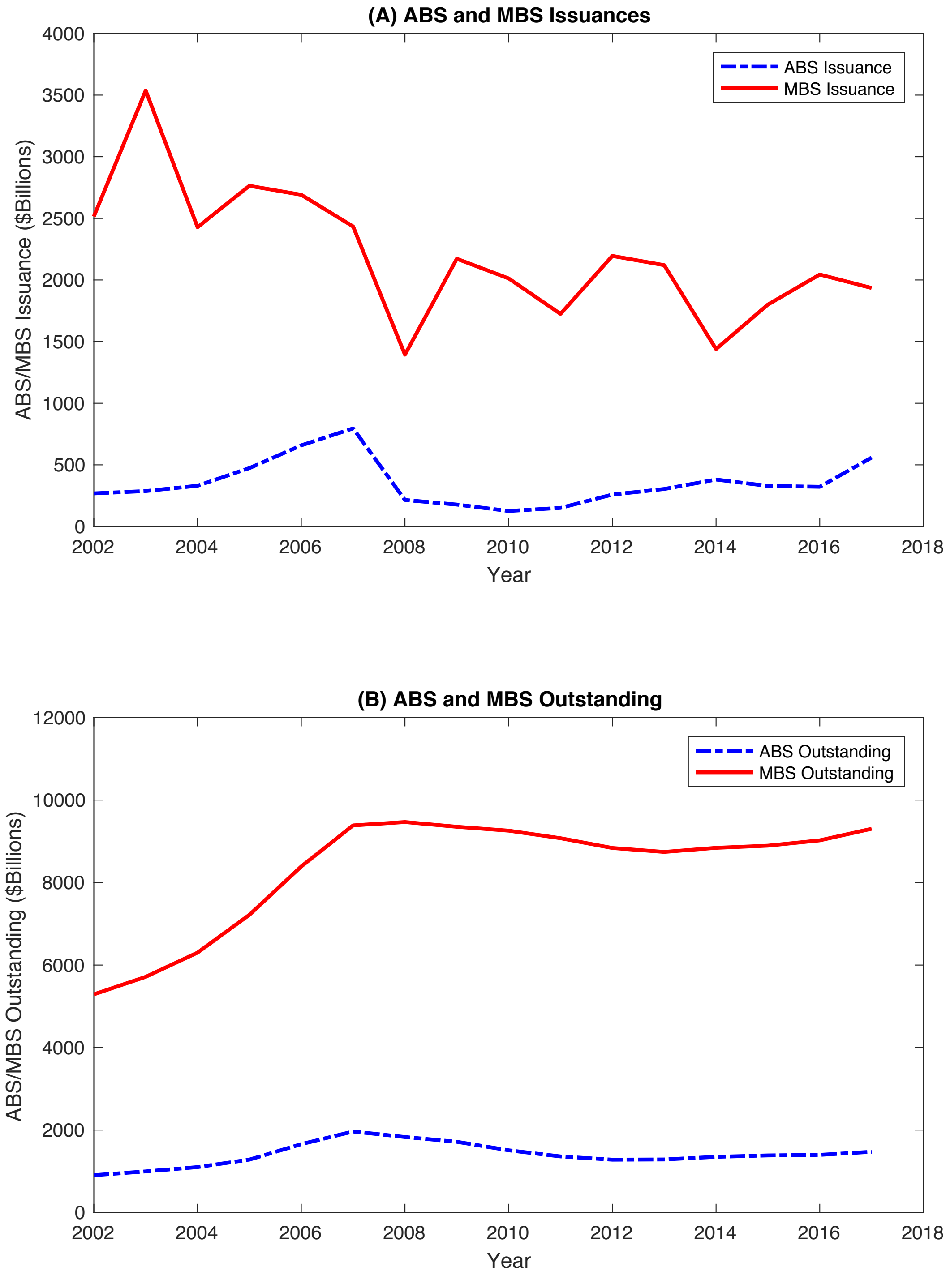

FIGURE 2.1: **Securitisation Market in the United States**
This figure presents the main developments in the US securitisation market between 2002 and 2017. Panel (A) shows issuances of Asset-Backed Securities (ABS) and Mortgage-Back Securities (MBS). Panel (B) shows outstanding amounts of Asset-Backed Securities (ABS) and Mortgage-Back Securities (MBS). All amounts are in billions of US Dollars. Data Source: Securities Industry and Financial Markets Association (SIFMA).

increase in the portion of industry income generated from fees-based activities (such as securitisation) rather than interest-generating activities starting from the 1980s. This trend has fundamentally altered the risk-return profiles of US banks over the last few decades (DeYoung and Roland, 2001). Particularly, banks cost of production were static or declining and there has been an increase in total revenues from traditional and non-traditional sources. This meant that by the mid-2000s, US banks profitability was very strong (Carlson and Weinbach, 2007). Indeed, until mid-2007 it was widely perceived that the US banking system was sound and performing well, particularly because banks capital holdings and profitability appeared to be high and at record levels. Nevertheless, Clark et al. (2007) emphasise how the increasingly fee-focused strategies of large US banks expose these banks to economic and business cycle volatility. With the onset of the mortgage crisis, problems in the housing market spilled over to the banking industry. The increased number of foreclosures and defaults in mortgages led to a decline in the value of securitised assets and reduced investors appetite for such securities and accordingly problems within the US banking industry (Gerardi et al., 2008).

In the US, securitisation origins go back to the early 1970s, when Government National Mortgage Association (Ginnie Mae) started to sell mortgage loans (Marques-Ibanez and Scheicher, 2009). Then, in the 1980s, the market grew with the issuances of securities by the semi-governmental agencies, Federal Home Loan Mortgage Corporation (Freddie Mac) and the Federal National Mortgage Association (Fannie Mae). Initially, securitisation processes included mortgage loans forming what is known as Mortgage Backed Securities (MBS). Later, they expanded to include other types of loans forming what is known as Asset Backed Securities (ABS). Furthermore, in the run-up to the 2008 credit crisis, more sophisticated forms of securitisation were developed such as Collateralised Mortgage Obligations (CMO). Securitisation activities played a pivotal role for the housing market in the run-up to the credit crisis of 2008 as the Asset Backed Securities (ABS) and covered bonds provided between 20 and 60 per cent of the funding for new residential mortgage loans originated in mature economies (International Monetary Fund, 2009).

Figure 2.1 presents the issuances and outstanding amounts of ABS and MBS in the US between 2002 and 2017. Historically, the MBS activities have dominated the securitisation market. The total volume of outstanding MBS in the US increased from $347 million in 1970 to nearly $8.92 trillion at the end of 2016, while the ABS market moved from $1.2 billion in 1985 to nearly $1.33 trillion at the end of 2016 (Securities Industry and Financial Markets Association, 2016). Also, it is worth noting that the outstanding securitisation amounts reached a peak of $11 trillion at the end of 2007, exactly before the onset of the credit crisis of 2008. In addition, the growth in securitisation activities was rapid in the run-up to the global financial crisis, but contracted sharply since the financial crisis in 2008 as shown by the large declines in the securitisation issuances. For example, securitisation issuance, including agency and non-agency MBS and ABS, totalled $2.2 trillion in 2016 which is equivalent to around two-thirds of the pre-crisis annual rate, and mainly driven by agency MBS.

2.2.2 The Data

In this subsection, we provide an overview of the data sample and variables used in our analysis.

2.2.2.1 Sample

This chapter considers the effect of securitisation activities on the profitability and risk of banks, and how the changes that securitisation causes in bank performance affect its stability. We further consider how the impact of securitisation on bank performance and stability depends on the prevailing monetary policy.

We obtain data on securitisation activities of the U.S commercial banks from the Reports of Condition and Income (Call Reports), which are available quarterly from the Federal Financial Institutions Examination Council (FFIEC).[3] Given that these detailed information on securitisation activities started to be required from reporting banks from the second quarter of 2001, our sample covers the period from 2001:Q2 through 2017:Q4. We also use the Call Reports data for other information about bank profitability and risk. In addition, our monetary policy and macroeconomic data comes from the Federal Reserve Economic Data (FRED), while data on the U.S banking industry is retrieved from the World Development Indicator (WDI) database provided by the World Bank.

When constructing the sample, bank-quarters with missing information on total assets, liquidity, loans, deposits, capital, and net income are excluded from the data set. Exploring the data set shows that securitisation activities of small banks are infrequent and insignificant. Therefore, we also exclude any bank-quarters with total assets less than $500 million. In addition, to ensure that the sample is as balanced as possible, we exclude banks that are acquired through a merger or acquisition using bank mergers data from the Federal Reserve National Information Center. Specifically, we exclude the target bank in the quarters before a merger. Furthermore, to prevent the possibility of outliers driving the results, quarterly variables computed from the sample are winsorised at the 1% level, that is, the smallest and largest 1% of the values of each variable is replaced with the closest value. The final data set contains 81,326 bank-quarters. To analyse differences in the securitisation effects over the sample period, we separate the sample into two subsamples: 2001:Q2-2008:Q4 and 2009:Q1-2017:Q4. The first period represents tight monetary policy with relatively high interest rates and

[3] The data are available as complete balance sheet, income statement, and detailed supporting schedules for each reporting bank. Data about securitisation activities of the reporting banks are included in a separate schedule for off-balance-sheet items (RC-S).

the second period represents a loose monetary policy with relatively low interest rates. In the subsections below, we discuss these data and variables in more detail.

2.2.2.2 Bank Securitisation Activities

The main explanatory variable in our analysis is the amount of outstanding securitisation. We measure securitisation by the ratio of all outstanding securitised loans to total assets. Further, for robustness we divide outstanding securitisation into mortgage-backed securitisation which includes both residential and commercial mortgage-backed securitised loans, and asset-backed securitisation which includes consumer credit, auto loans, credit cards, and commercial and industrial loans. While scaling securitised loans by total assets or total loans yields similar empirical results, we opt to use the ratio of securitisation to total assets. Scaling by total assets allows for better interpretation of results given that other bank-level variables are calculated as ratios of total assets.

2.2.2.3 Bank Profitability and Risk

Given our focus on the effects of securitisation on bank performance, we use two measures of bank profitability that are widely used in literature: return on assets and net interest margin (Berger, 1995). Return on assets is the traditional measure of bank profitability that measures how well bank assets are being used to generate profits. It is calculated as the ratio of net income to total assets, hence, it corrects for bank size. Securitisation activities are expected to affect return on assets directly given that income from securitisation is included when calculating net income of banks. Net interest margin is another useful measure of bank profitability that is calculated as the difference between interest income and interest expenses scaled by total assets. Securitisation activities are expected to affect net interest margin indirectly through their impact on the composition and quality of the loan portfolio which in turn determines the interest income. Using these two different measures provides an advantage as it allows us to capture the overall effects of securitisation on bank profitability when using return on assets, while we can assess the effects of securitisation on the profitability of the bank loan portfolio using net interest margin.

In addition, given our focus on the effects of securitisation on bank performance, we use two different proxies for bank risk following (Casu et al., 2013) including the ratio of risk-weighted assets and allowances ratio. The first measure is calculated as the ratio of risk-weighted assets to total assets and captures the overall riskiness of bank assets. This measure is more suitable to account for the overall impact of securitisation on bank risk. Alternatively, we use the allowances ratio which is calculated as the ratio of allowance for loan losses to total assets as another proxy for bank risk. This measure captures the riskiness of the bank loan portfolio, hence enables us to focus on the effects of securitisation on the riskiness of the bank loan portfolio as comparable to total assets.

2.2.2.4 Monetary Policy

Critical to our analysis is the role of monetary policy in determining the effect of securitisation on bank performance and stability. Specifically, to proxy the monetary policy stance, we use end of quarter effective federal funds rate provided by the Board of Governors Release H.15. The federal funds rate is the prevalent measure of monetary policy in empirical work and is well suited to capture the stance of monetary policy because it is sensitive to shocks to the supply of bank reserves and increases in its level represent monetary policy tightening (Bernanke and Blinder, 1992). Figure 2.2 presents the end-of-quarter effective federal funds rate in the United States over the sample period from 2001 to 2017. To analyse differences in the securitisation effects over the sample period, we use this measure to separate the sample into two sub-periods. The first sub-period starts from 2001:Q2 through 2008:Q4 and represents monetary policy tightening with

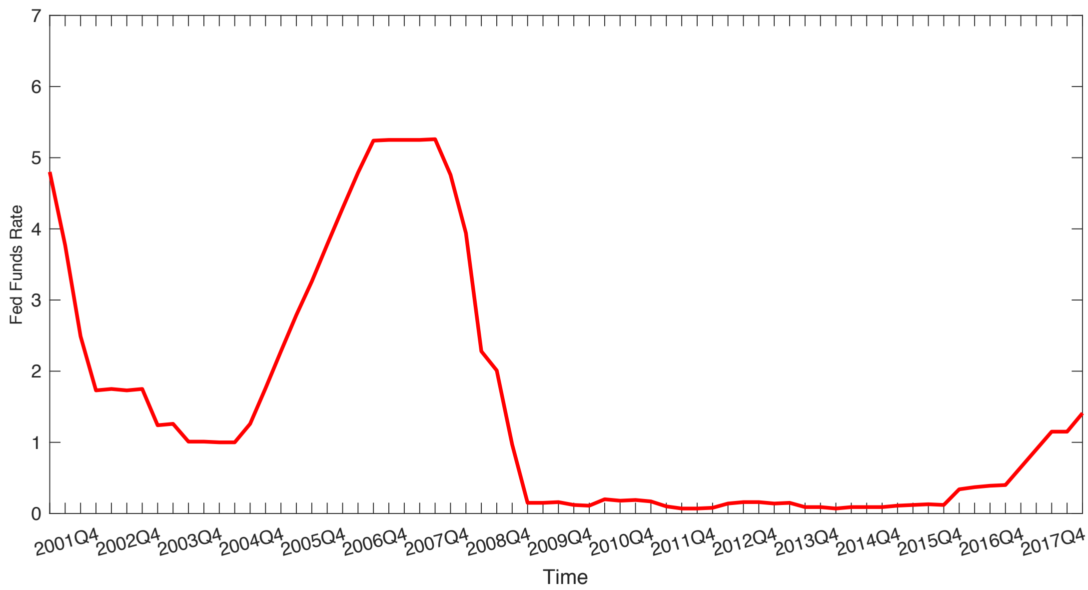

FIGURE 2.2: **Federal Funds Rate in the United States**
This figure presents the end-of-quarter effective federal funds rate in the United States over the sample period from 2001 to 2017. Data Source: Federal Reserve Economic Data (FRED).

relatively high federal funds rates. The second sub-period starts from 2009:Q1 through 2017:Q4 and represents monetary policy loosening with relatively low federal funds rates.

2.2.2.5 Summary Statistics

Table 2.1 presents summary statistics for various variables in our sample. We report the mean, standard deviation, minimum and maximum values for each variable for the full sample and for the two sub-samples of high and low interest rates. Panel A shows that the composition of banks' balance sheets has changed over time. Of the noticeable changes is the average decline in return on assets from 0.75% to 0.47%, while the net interest margin has slightly declined from 2.3% to 2.07%, on average. Meanwhile, the overall riskiness of bank assets has improved as measured by risk-weighted assets (77% versus 71%), while the allowances ratio has remained stable at around 1.5% and 1.7%.

TABLE 2.1: Summary Statistics

	2001-2017					2001-2008					2009-2017				
	N	Mean	Std. Dev.	Min	Max	N	Mean	Std. Dev.	Min	Max	N	Mean	Std. Dev.	Min	Max
Panel A: Bank Level Variables															
Return on Assets	81,326	0.0058	0.0128	-0.4467	0.7289	32,472	0.0075	0.0144	-0.4467	0.5504	48,854	0.0047	0.0114	-0.4267	0.7289
Net Interest Margin	81,326	0.0216	0.0140	-0.0289	0.3628	32,472	0.0230	0.0149	-0.0289	0.2895	48,854	0.0207	0.0132	-0.0149	0.3628
Risk-Weighted Assets	81,326	0.7209	0.1610	0.0001	1.6223	32,472	0.7430	0.1816	0.0856	1.6223	48,854	0.7063	0.1439	0.0001	1.5323
Allowance Ratio	81,326	0.0158	0.0175	0.0000	0.1740	32,472	0.0146	0.0198	0.0000	0.1740	48,854	0.0167	0.0157	0.0000	0.1510
Interest expense Ratio	81,326	0.0094	0.0090	0.0000	0.3628	32,472	0.0159	0.0101	0.0000	0.2538	48,854	0.0050	0.0050	0.0000	0.3628
Liquidity ratio	81,326	0.2654	0.1512	0.0005	0.9868	32,472	0.2505	0.1518	0.0005	0.9568	48,854	0.2753	0.1499	0.0006	0.9868
Size	81,326	14.1642	1.2693	9.6469	21.4901	32,472	14.1592	1.2739	9.6469	21.0417	48,854	14.1675	1.2662	9.7042	21.4901
Total risk based capital ratio	81,326	0.1456	0.1340	0.0000	0.5556	32,472	0.1480	0.1217	0.0000	0.5056	48,854	0.1441	0.1146	0.0000	0.5556
Equity ratio	81,326	0.1092	0.0582	0.0114	0.8698	32,472	0.1055	0.0639	0.0114	0.8498	48,854	0.1115	0.0530	0.0143	0.8698
Trading Assets ratio	81,326	0.0022	0.0218	0.0000	0.3393	32,472	0.0035	0.0302	0.0000	0.3393	48,854	0.0012	0.0112	0.0000	0.3093
Loan to Assets ratio	81,326	0.6645	0.1613	0.0000	0.9005	32,472	0.6687	0.1708	0.0000	0.9005	48,854	0.6617	0.1547	0.0000	0.8654
Deposits to Assets ratio	81,326	0.7762	0.1387	0.0000	0.9554	32,472	0.7405	0.1672	0.0000	0.9154	48,854	0.7999	0.1098	0.0000	0.9554
Panel B: Securitisation Activities															
Securitisation to total assets	7,593	0.2829	1.2456	0.0000	69.1727	3,807	0.3797	1.6688	0.0000	69.1727	3,786	0.1856	0.5411	0.0000	4.6822
MBS	7,593	0.0842	0.2992	0.0000	4.6324	3,807	0.0497	0.1362	0.0000	2.2801	3,786	0.1190	0.3982	0.0000	4.6324
ABS	7,593	0.1987	1.2169	0.0000	69.1727	3,807	0.3300	1.6725	0.0000	69.1727	3,786	0.0667	0.3501	0.0000	4.1783
Net Securitisation Income on Assets	3,682	0.0131	0.0501	-0.0719	0.5586	2,376	0.0187	0.0608	-0.0719	0.5586	1,306	0.0029	0.0135	-0.0646	0.2309
Panel C: Macroeconomic Variables															
GDP Growth	67	1.8676	2.3668	-8.2000	6.9000	31	1.7969	2.7485	-8.2000	6.9000	36	1.9306	2.0058	-5.4000	5.2000
Federal Funds Rate	67	1.4591	1.7059	0.0700	5.2600	31	2.7847	1.6531	0.1500	5.2600	36	0.2808	0.3400	0.0700	1.4100
Boone Indiator	67	-0.0554	0.0140	-0.0853	-0.0397	31	-0.0675	0.0099	-0.0853	-0.0562	36	-0.0446	0.0060	-0.0554	-0.0397
ROA_System	67	0.0023	0.0012	-0.0027	0.0034	31	0.0026	0.0014	-0.0027	0.0034	36	0.0021	0.0010	-0.0009	0.0028
NSI_System	67	0.0003	0.0003	0.0000	0.0007	31	0.0005	0.0001	0.0002	0.0007	36	0.0000	0.0000	0.0000	0.0002

When comparing statistics for securitisation activities between the two sub-periods as shown in panel B, we notice a significant decline in outstanding securitised loans from 37.97% to 18.56%. The decline is more severe for asset backed securitisation as compared to mortgage-backed securitisation. In addition, the net securitisation has witnessed a severe decline from 1.9% to 0.29%. This is consistent with the impairment of the securitisation markets and the decline in issuances following the credit crisis. Turning to monetary policy, panel C shows that federal funds rate has declined significantly from 2.78% in the first sub-period as compared to 0.28% in the second sub-period.

2.3 The Trade-off Between Profitability and Risk

In this section, we empirically evaluate the relationship between profitability and risk of banks that engage in securitisation activities. Literature on the determinates of bank profitability is voluminous with a focus on two broad groups of determinants: internal and external. Internal determinants of bank profitability are those factors that can be altered by the bank decisions, while external determinants include industry-specific and macroeconomic factors that are not under the control of banks.

The literature reports a variety of internal factors that determine bank profitability with bank risk being a major factor that affects profitability. The predominant types of risks that affect banks are credit risk, market risk, and liquidity risk. Higher credit risk implies higher loan loss provisions, and accordingly lower returns achieved by banks. Hence, excess exposure to credit risk reduces profitability (Bourke, 1989; Miller and Noulas, 1997). The impact of liquidity risk on bank profitability is less straightforward. Liquidity can affect bank profitability in both directions. It can reduce profitability when liquid assets with lower rates of return increase (Guru et al., 2002; Molyneux and Thornton, 1992), still some empirical research shows a positive impact of liquidity on bank profitability (Bourke, 1989; Pasiouras and Kosmidou, 2007). Bank size captures the ability of a bank to reduce costs due to economies of scale and scope and hence increasing profitability (Goddard et al., 2004). The level of capital can also affect bank profitability. It can improve profitability if it improves the soundness of the bank resulting in lower cost of funding from other sources (Demirgüç-Kunt and Huizinga, 1999; Pasiouras and Kosmidou, 2007) or it can reduce bank profitability if banks are required to increase their balance of high quality assets that qualify as capital, but have relatively low rates of return (Dietrich and Wanzenried, 2011). In addition, some studies show that cost of funding has a direct and positive impact on profitability (Berger, 1995; Demirgüç-Kunt and Huizinga, 1999; Kosmidou et al., 2007; Kosmidou, 2008). The balance sheet composition can also affect bank profitability. For instance, the higher the loans to assets ratio, the higher the bank profitability because lending portfolio is expected to generate higher returns compared to other asset categories.

Additionally, competition is the main industry-specific determinant of bank profitability. It might improve efficiency leading to cost reductions and higher profitability (Claessens and Laeven, 2004), or it might force banks to charge lower rates on lending resulting in lower profitability (Martinez-Miera and Repullo, 2010). Furthermore, real GDP growth is a macroeconomic determinant of bank profitability. It captures the improvement in business conditions and increased demand for lending leading to higher profitability as shown by (Demirgüç-Kunt and Huizinga, 1999). Inflation measures macroeconomic stability and can also affect bank profitability. The reason is that unanticipated inflation can lead to inaccurate pricing of loans and increase in loan loss rates which implies lower profitability (Lee and Hsieh, 2013).

2.3.1 Econometric Specification

As discussed above, we aim to investigate the relationship between profitability and risk of banks that engage in securitisation activities in comparison with other banks that do not participate in securitization market. Specifically, we investigate the change in profitability of banks in a specific quarter in response to changes in bank risk, depending on the banks' exposure to the securitization activities. Further, we expect bank profitability to show dependency over time. Therefore, we estimate the following dynamic panel data model:

$$PROFIT_{i,t} = \alpha_i + \beta_1\, PROFIT_{i,t-1} + \beta_2\, iSEC + \beta_3\, iSEC * RISK_{i,t-1} + \gamma\, \mathbf{X}_{i,t-1} + \theta_t + \varepsilon_{i,t} \tag{2.1}$$

where $PROFIT_{i,t}$ denotes bank profitability, $RISK_{i,t}$ denotes bank risk, and $\mathbf{X}_{i,t}$ is a vector of control variables. $iSEC$ is a binary indicator variable that takes the value 1 if the bank has securitisation activities in a given quarter and zero otherwise. The sub-indices i and t denote banks and time, respectively. The parameters to be estimated are α_i, β_1, β_2. β_3, and γ. θ_t is a time-specific fixed effect. $\varepsilon_{i,t}$ is an error term. In this specification, we specifically focus on β_3, the interaction of the banks risk with the exposure of the bank to the securitization activities.

We use two different measures for profitability: net interest margin and return on assets. We also use two different measures for bank risk including the one-period lagged ratio of risk-weighted assets to total assets and the one-period lagged ratio of loan loss allowance to total assets. In addition, to help mitigate omitted variables bias, we control for bank-specific, industry-specific, and macroeconomic factors that might affect bank profitability, risk or both. First, we include the natural log of total assets to control for bank size which is expected to affect its profitability. This can be due to the economies of scale or the ability of large banks to lend more (Goddard et al., 2004), and accordingly to have better access to the securitisation market due to their large and homogeneous loans portfolios (Loutskina, 2011). Second, we include in the regression the equity ratio calculated as the ratio of Tier 1 risk-based capital to total assets. Maintaining high capital levels provides the bank with protection in case of a banking crisis, and against different risks resulting from the bank exposure to outstanding securitisations. Moreover, the protection provided by capital buffer supports the bank's profitability in the long run (Berger, 1995). Third, to control for balance sheet composition, we include two measures: the ratio of trading assets to total assets to account for other sources of bank profitability other than lending, and the ratio of deposits to total assets to account for stability of bank funding. Fourth, to control for competition in the banking system, we include the Boone indicator calculated as the elasticity of bank profits to marginal costs (Boone, 2008). The more negative the Boone indicator, the higher the degree of competition in the banking system because the effect of reallocation is stronger. Estimations of this measure are retrieved from World Development Indicator (WDI) database provided by the World Bank. Finally, we include the rate of growth in real Gross Domestic Product (GDP) to account for macroeconomic developments that could affect bank profitability and risk. It is expected that changes in GDP growth capture the effects of the business cycle on bank's profitability (Demirgüç-Kunt and Huizinga, 1999). All variables are lagged for one period to allow the effects of securitisation activities to be realised in bank profitability and risk and to avoid simultaneity.

We estimate the model presented in Equation 2.1 using the dynamic system generalised method of moments (System-GMM) estimator in order to obtain consistent and unbiased estimates of the model parameters. This estimator was introduced by (Arellano and Bond, 1991) and further developed in (Arellano and Bover, 1995) and (Blundell and Bond, 1998). Using the System-GMM estimator provides several advantages in estimating our model including its ability to correct for different sources endogeneity (Wintoki et al., 2012). First, it accounts for simultaneity that stems from the fact that financial variables are likely to be determined simultaneously. For instance, for banks to achieve specific levels of profitability, bank risk taking can be adjusted which might hide the actual relation between profitability and risk. Second, the System-GMM estimator accounts for unobserved heterogeneity where some variables are omitted because they are unobservable, which could result in inconsistent estimates. An example of these unobservable variables include management skills and ability that cannot be measured easily. Third, the System-GMM estimator accounts for dynamic endogeneity in dynamic panel data models. Specifically, including the lagged dependent variable as a regressor makes it endogenous to fixed effects in the error terms. This gives rise to dynamic endogeneity in the model specification, resulting in positive correlation between the regressor and error terms which violates the assumptions required for traditional estimators such as ordinary least squares. Thus, employing the System-GMM estimator to estimate our model provides the most consistent estimates as it accounts for the three aforementioned sources of endogeneity.

The System-GMM estimator builds a system of two equations; one in differenced variables to eliminate the potential sources of omitted variables bias in estimation and the original equation in levels to improve the efficiency of estimation (Arellano and Bover, 1995). The method then uses lags of the dependent and independent variables as instruments. In particular, variables in levels are instrumented with suitable lags of their own first differences, while the differenced variables that are not strictly exogenous are instrumented with all their available lags in levels. To assess the model specification we use two tests. First, to assess autocorrelation between error terms and regressors, we use the Arellano-Bond test for autocorrelation which is applied to the differenced residuals in order to purge the unobserved and perfectly autocorrelated individual-level effect (Arellano and Bond, 1991). Second, to assess the validity of instruments, we use the Hansen J-statistic for overidentifying restrictions which tests whether the instruments, as a group, appear exogenous, and is robust to heteroskedasticity and autocorellation (Roodman, 2009). Further, we use two-step robust estimation which is asymptotically more efficient than one-step estimation. Finally, to compensate for the downward-biased standard errors which result when using two-step System-GMM (Arellano and Bond, 1991; Blundell and Bond, 1998), we implement the finite-sample correction method derived by (Windmeijer, 2005) to the two-step covariance matrix.

2.3.2 Empirical Results

Table 2.2 reports the results of estimating the model specified in Equation 2.1. The results confirm the dependency in bank profitability and justify our use of a dynamic panel data model. Columns (1) and (2) use risk weighted assets and allowance ratio as measures of bank risk, respectively. They show that on average a 1% increase in return on assets is associated with an increase of 0.47% and 0.52% in return on assets in the following period, respectively. Similar results are obtained when using net interest margin as the measure of bank profitability. Turning to assess the impact of bank risk on its profitability, we focus on the coefficient on the interaction variable between $iSEC$ and bank risk. Columns (1) and (2) show the results using return on assets as the profitability measure. Since both profitability and risk measures are scaled by total assets, column (1) shows that a 1% increase in risk-weighted assets increases return on assets by about 0.09%. This increase is for the securitiser banks ($iSEC$ is 1) compared to non securitisers ($iSEC$ is 0). Similarly, column (2) shows that a 1% increase in allowances ratio increases return on assets by about 0.29%. The results hold when using net interest margin as our measure of bank profitability with even larger magnitude of impact. Column (3) shows that net interest margin of a securitiser bank increases by about 0.27% on average when its risk-weighted assets increases by 1%. Finally, column (4) shows that net interest margin of a securitiser bank increases by about 0.69% on average when its allowance ratio increases by 1%. It is worth mentioning that the impact of bank risk becomes even larger when we focus on the riskiness of the loan portfolio measured by the loan loss allowance ratio as compared to the overall riskiness of bank assets as measured by the risk-weighted assets ratio. This implies that the contribution of the bank's loan portfolio to its profitability is larger compared to other assets categories.

2.3.3 Further Evidence

To check the robustness of our results presented above, we perform two further analyses. In the first analysis, we examine whether the results hold for two sub-periods: the first is 2001:Q2-2008:Q4 which represents the run-up to the global financial crisis in 2008, and second is 2009:Q1-2017:Q4 which represents the period that followed the crisis. Our motivation is to study whether the structural changes in the banking industry and securitisation markets after the crisis have altered the relation between bank profitability and risk. The results of these specifications are presented in Table 2.3. Two findings are worth mentioning based on these results. First, the main results hold before and after the financial crisis: there is a positive and significant relationship between bank risk and bank profitability for securitiser banks compared to non-securitiser banks. This result holds when using different measures for both bank risk and profitability. Second, there is a decline in the impact of risk on profitability in the period that followed the crisis. For example, a 1% increase in risk-weighted assets after the crisis leads to an increase of 0.02% in return on assets compared to 0.16% before the crisis.

TABLE 2.2: **The Impact of Bank Risk on Bank Profitability I.**
This table shows the results of examining the impact of bank risk on bank profitability for securitiser compared to non-securitiser banks. Model specifications in columns 1 through 4 are estimated using the System-GMM estimation method. The sample includes quarterly data from 2001:Q2 through 2017;Q4. *Return_on_Assets* is the return on assets calculated as the ratio of net income to total assets. *Net_Interest_Margin* is the net interest margin calculated as the ratio of net interest income to total assets. $iSEC$ is an indicator variable that takes a value of 1 if the bank has securitisation activities, and a value of 0 otherwise. *RWA* is the ratio of risk-weighted assets to total assets. *ALLOW* is the ratio of loan loss allowance to total assets. *Size* is the natural logarithm of total assets. *Equity* is the ratio of Tier 1 risk-based capital ratio to total assets. *Trading_Assets* is the ratio of trading assets to total assets. *Deposits* is the ratio of bank deposits to total assets. *Boone_Ind* is the quarterly estimation of Boone indicator for the banking system. *GDP_Growth* is the rate of growth in real gross domestic product. Standard errors in parentheses. *,**,*** denote statistical significance at the 10%, 5%, and 1% level respectively.

	$Return\_on\_Assets_t$		$Net\_Interest\_Margin_t$	
	(1)	(2)	(3)	(4)
$Return\_on\_Assets_{t-1}$	0.4747***	0.5204***		
	(0.0031)	(0.0023)		
$Net\_Interest\_Margin_{t-1}$			0.089***	0.0928***
			(0.0012)	(0.0008)
iSEC	-0.0665***	-0.0046***	-0.1992***	-0.0451***
	(0.005)	(0.0004)	(0.0148)	(0.003)
iSEC× RWA_{t-1}	0.0893***		0.2659***	
	(0.0065)		(0.0193)	
iSEC× $ALLOW_{t-1}$		0.2939***		0.6885***
		(0.0182)		(0.1716)
$Size_{t-1}$	0.0002***	0.0001**	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$Equity_{t-1}$	0.0232***	0.0187***	0.0052	0.0046
	(0.0026)	(0.0016)	(0.0039)	(0.0044)
$Trading\_Assets_{t-1}$	-0.0347***	-0.0062	-0.1497***	-0.0135
	(0.0116)	(0.004)	(0.0395)	(0.014)
$Deposits_{t-1}$	0.002***	0.0013***	0.0224***	0.0147***
	(0.0007)	(0.0003)	(0.0018)	(0.001)
$Boone\_Ind_{t-1}$	-0.0089***	-0.0239***	-0.0088***	-0.0733***
	(0.0028)	(0.0015)	(0.0033)	(0.0023)
GDP_Growth_{t-1}	0.0005***	0.0005***	0.0007***	0.0007***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
# of Observations	77787	77251	77787	77251
# of Banks	2687	2672	2687	2672
# of Instruments	51	51	51	51
AR(1)	0.000	0.000	0.000	0.000
AR(2)	0.586	0.509	0.071	0.139
Hansen Test	0.082	0.201	0.342	0.243

TABLE 2.3: **The Impact of Bank Risk on Bank Profitability II.**

This table shows the results of examining the impact of bank risk on bank profitability for securitiser compared to non-securitiser banks over two sub-periods: 2001:Q2-2008:Q4 and 2009:Q1-2017:Q4. Model specifications in columns 1 through 8 are estimated using the System-GMM estimation method. The sample in columns 1 through 4 includes quarterly data from 2001:Q2 through 2008:Q4. The sample in columns 5 through 8 includes quarterly data from 2009:Q1 through 2017:Q4. *Return_on_Assets* is the return on assets calculated as the ratio of net income to total assets. *Net_Interest_Margin* is the net interest margin calculated as the ratio of net interest income to total assets. $iSEC$ is an indicator variable that takes a value of 1 if the bank has securitisation activities, and a value of 0 otherwise. *RWA* is the ratio of risk-weighted assets to total assets. *ALLOW* is the ratio of loan loss allowance to total assets. *Size* is the natural logarithm of total assets. *Equity* is the ratio of Tier 1 risk-based capital ratio to total assets. *Trading_Assets* is the ratio of trading assets to total assets. *Deposits* is the ratio of bank deposits to total assets. *Boone_Ind* is the quarterly estimation of Boone indicator for the banking system. *GDP_Growth* is the rate of growth in real gross domestic product. Standard errors in parentheses. *,**,*** denote statistical significance at the 10%, 5%, and 1% level respectively.

	2001-2008				2009-2017			
	Return_on_Assets$_t$		Net_Interest_Margin$_t$		Return_on_Assets$_t$		Net_Interest_Margin$_t$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Return_on_Assets$_{t-1}$	0.3589***	0.4763***			0.4869***	0.4676***		
	(0.0051)	(0.0031)			(0.0047)	(0.005)		
Net_Interest_Margin$_{t-1}$			0.1687***	0.1969***			0.1835***	0.2252***
			(0.0023)	(0.0021)			(0.0015)	(0.0009)
iSEC	-0.1267***	-0.0093***	-0.0038***	-0.0018***	-0.014*	0.0106***	-0.2119***	-0.0006*
	(0.0106)	(0.0007)	(0.0005)	(0.0004)	(0.0072)	(0.0015)	(0.0198)	(0.0003)
iSEC×RWA$_{t-1}$	0.163***		0.896***		0.02**		0.2928***	
	(0.0133)		(0.0676)		(0.01)		(0.027)	
iSEC×ALLOW$_{t-1}$		0.696***		0.6305***		0.2259***		0.3423***
		(0.0279)		(0.0578)		(0 .0216)		(0.024)
Size$_{t-1}$	0.0002**	0.0001	0.0005***	0.0005***	0.0002***	0.0002	0.0004***	0.0001**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Equity$_{t-1}$	0.0188***	0.01***	0.0143***	0.0192***	0.025***	0.0193***	0.0121*	0.0637***
	(0.0041)	(0.0019)	(0.005)	(0.0052)	(0.0031)	(0.0033)	(0.0067)	(0.0046)
Trading_Assets$_{t-1}$	-0.0802***	-0.0161***	-0.0262***	-0.0302***	-0.0075	0.0075	-0.2052***	-0.0516***
	(0.0193)	(0.0054)	(0.0083)	(0.0087)	(0.0069)	(0.0112)	(0.0273)	(0.0108)
Deposits$_{t-1}$	0.008***	0.001*	0.014***	0.013***	-0.0011*	-0.0027***	0.0134***	0.0044***
	(0.0014)	(0.0005)	(0.0008)	(0.0008)	(0.0006)	(0.0007)	(0.002)	(0.0008)
Boone_Ind$_{t-1}$	0.0257***	0.0032	0.0065**	0.0121***	-0.0427***	-0.0275***	-0.1734***	-0.1378***
	(0.0067)	(0.0034)	(0.0033)	(0.0033)	(0.0057)	(0.0053)	(0.0051)	(0.0021)
GDP_Growth$_{t-1}$	0.0004***	0.0004***	0.0009***	0.0008***	0.0004***	0.0004***	0.0011***	0.0007***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
# of Observations	30321	30102	30321	30102	47466	47149	47466	47149
# of Banks	1783	1772	1783	1772	2144	2131	2144	2131
# of Instruments	29	29	29	29	34	34	34	34
AR(1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2)	0.432	0.467	0.142	0.113	0.612	0.567	0.093	0.112
Hansen Test	0.071	0.021	0.432	0.321	0.001	0.113	0.231	0.481

TABLE 2.4: **The Impact of Bank Risk on Bank Profitability III.**

This table shows the results of examining the impact of bank risk on bank profitability for mortgage-backed securitiser compared to non-mortgage-backed securitiser banks and for asset-backed securitiser compared to non-asset-backed securitiser banks. Model specifications in columns 1 through 8 are estimated using the System-GMM estimation method. The sample period includes quarterly data from 2001:Q2 through 2017:Q4. *Return_on_Assets* is the return on assets calculated as the ratio of net income to total assets. *Net_Interest_Margin* is the net interest margin calculated as the ratio of net interest income to total assets. *iMBS (iABS)* is an indicator variable that takes a value of 1 if the bank has mortgage-backed (asset-backed) securitisation activities, and a value of 0 otherwise. *RWA* is the ratio of risk-weighted assets to total assets. *ALLOW* is the ratio of loan loss allowance to total assets. *Size* is the natural logarithm of total assets. *Equity* is the ratio of Tier 1 risk-based capital ratio to total assets. *Trading_Assets* is the ratio of trading assets to total assets. *Deposits* is the ratio of bank deposits to total assets. *Boone_Ind* is the quarterly estimation of Boone indicator for the banking system. *GDP_Growth* is the rate of growth in real gross domestic product. Standard errors in parentheses. *,**,*** denote statistical significance at the 10%, 5%, and 1% level respectively.

	Return_on_Assets$_t$				Net_Interest_Margin$_t$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Return_on_Assets$_{t-1}$	0.5241***	0.512***	0.4699***	0.5185***				
	(0.0023)	(0.0023)	(0.003)	(0.0023)				
Net_Interest_Margin$_{t-1}$					0.2003***	0.2173***	0.1015***	0.1013***
					(0.0013)	(0.0007)	(0.001)	(0.0007)
iMBS	-0.0048***	-0.0091***			-0.2601***	-0.0227***		
	(0.0013)	(0.0016)			(0.0382)	(0.0042)		
iMBS×RWA$_{t-1}$	0.0621***				0.2651***			
	(0.0063)				(0.0526)			
iMBS×ALLOW$_{t-1}$		0.1901***				0.3388***		
		(0.0084)				(0.2973)		
iABS			-0.1051***	-0.0059***			-0.2939***	-0.0721***
			(0.0068)	(0.0006)			(0.0215)	(0.0041)
iABS×RWA$_{t-1}$			0.1317***				0.3567***	
			(0.0081)				(0.0252)	
iABS×ALLOW$_{t-1}$				0.3377***				0.4567***
				(0.0272)				(0.1951)
Size$_{t-1}$	0.0003***	0.0001	0.0001***	0.0002*	0.0003***	0.0001	0.0002*	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Equity$_{t-1}$	0.0238***	0.0213***	0.0208***	0.0179***	0.0119*	0.039***	0.0031	0.0018
	(0.0023)	(0.0019)	(0.0025)	(0.0016)	(0.0062)	(0.0043)	(0.0036)	(0.0041)
Trading_Assets$_{t-1}$	-0.0021	-0.0034	-0.0408***	-0.0066	-0.1328**	-0.0198***	-0.1465***	-0.0148
	(0.0047)	(0.0026)	(0.0123)	(0.0042)	(0.0544)	(0.006)	(0.0383)	(0.0134)
Deposits$_{t-1}$	0.0013***	0.0019***	0.0015**	0.0016***	0.017***	0.0095***	0.0187***	0.012***
	(0.0003)	(0.0003)	(0.0006)	(0.0003)	(0.0017)	(0.0007)	(0.0016)	(0.001)
Boone_Ind$_{t-1}$	-0.0223***	-0.0133***	-0.0042	-0.0214***	-0.0503***	-0.0715***	-0.0028	-0.0531***
	(0.0015)	(0.0019)	(0.0028)	(0.0015)	(0.0039)	(0.0019)	(0.0032)	(0.0022)
GDP_Growth$_{t-1}$	0.0005***	0.0004***	0.0004***	0.0005***	0.0007***	0.0006***	0.0006***	0.0007***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
# of Observations	77787	77251	77787	77251	77787	77251	77787	77251
# of Banks	2687	2672	2687	2672	2687	2672	2687	2672
# of Instruments	51	51	51	51	51	51	51	51
AR(1)	0.000	0.002	0.006	0.003	0.001	0.000	0.007	0.000
AR(2)	0.162	0.395	0.167	0,219	0.171	0.432	0.094	0.182
Hansen Test	0.281	0.163	0.404	0.361	0.242	0.387	0.165	0.612

This result also holds when using different measures for both bank risk and profitability.

In the second analysis, we examine whether the results hold for different types of securitisation activities. To this end, we estimate the model specified in Equation 2.1 after introducing two different indicator variables instead of $iSEC$. The first indicator variable is $iMBS$ that takes 1 if the bank has outstanding amounts of mortgage-backed securitisation, and takes 0 otherwise. The second indicator variable is $iABS$ that takes 1 if the bank has outstanding amounts of asset-backed securitisation, and takes 0 otherwise. The results of this specification are reported in Table 2.4. The results show that the main results presented above still hold for different types of securitisation activities. Bank risk significantly and positively affects bank profitability for both mortgage-backed and asset-backed securitiser banks compared to non-mortgage-backed and non-asset-backed securitiser banks, respectively. In addition, the results also show that the impact is larger for asset-backed securitisers compared to mortgage-backed securitisers. For example, a 1% increase in risk-weighted assets leads to an increase of 0.06% in return on assets for mortgage-backed securitisers compared to 0.13% for asset-backed securitisers. These results holds when using different measures for both bank risk and profitability.

2.4 Can Securitisation Explain the Profitability-Risk Trade-off?

The results presented in Section 2.3 establish that, for banks that engage in securitisation activities, to increase profitability they should expect to bear more risk. In this section, we extend the analysis to examine whether securitisation activities can explain why securitisers encounter this trade-off between profitability and risk. Our strategy of analyzing the role of securitisation in explaining this trade-off relies on simultaneously studying two channels through which securitisation affects both bank profitability and risk: liquidity and cost of funding.

There are various incentives for a bank to engage in securitisation activities including improving profitability and improving risk management. While several studies suggest that securitisation improves bank profitability (see Marques-Ibanez and Scheicher, 2012; Wolfe, 2000; Kopff and Lent, 1990; Thomas, 1999), the impact of securitisation on bank risk is twofold (Instefjord, 2005). On the one hand, it may reduce bank risk by shifting credit risk to the market and improving risk sharing opportunities (Cebenoyan and Strahan, 2004), reducing insolvency risk (Jiangli et al., 2008), or reducing credit risk by securitizing the worst loans while keeping high-quality loans (Mian and Sufi, 2009). On the other hand, securitisation may increase bank risk due to the increase in risk taking (Bedendo and Bruno, 2012), recourse and other seller-provided credit enhancements (Higgins and Mason, 2004), or due to retaining riskier loans while selling safer ones in response to regulatory requirements (Ambrose et al., 2005).

We study two channels through which securitisation affects both bank risk and profitability. The first channel is bank liquidity. Traditional incentives of securitisation entail improving liquidity as a primary objective because securitisation allows banks to liquidate illiquid assets and improve liquidity positions (Cardone-Riportella et al., 2010). However, Loutskina (2011) show that when banks have the option to securitise, they tend to reduce their holdings of liquid assets. Similarly, Loutskina and Strahan (2009) show that banks with large amounts of liquid holdings is more expected to grant loans that are difficult to securitise than to grant liquid loans. In other words, banks consider securitisation as another source of liquidity that is not counted in the traditional liquidity measures. Liquidity, in turn, impacts both bank profitability and risk. Banks may decide to hold liquid assets to reduce risks and to avoid bank failures (Imbierowicz and Rauch, 2014). Although liquid assets are usually associated with lower rates of return, empirical evidence on the impact of liquidity on bank profitability is ambiguous. While Bourke (1989) and Pasiouras and Kosmidou (2007) show a significantly positive relationship between liquidity and bank profitability, Guru et al. (2002) and Molyneux and Thornton (1992) report an opposite result.

The second channel is cost of funding. Securitisation provides banks with an opportunity to diversify funding sources, reduce the costs of external financing through debt and deposits, and accordingly to reduce the overall cost of funding (Pennacchi, 1988; Jones, 2000). In contrast, some studies suggest that securitisers might encounter higher cost of funding compared to other banks. This occurs when the potential benefits to banks in terms of reduced cost of funding are outweighed by the implicit and explicit costs resulting from recourse related to transactions (Higgins and Mason, 2004) or when banks provide credit risk enhancements to accompany securitisations (Casu et al., 2013). Cost of funding, in turn, impacts both bank profitability and risk. Banks with lower need for external funds, have lower cost of funding, lower cost of bankruptcy, and higher profitability (Berger, 1995; Demirgüç-Kunt and Huizinga, 1999). The main argument here is that the availability of securitisation as an internal source of funds reduces the sensitivity of the bank cost of funding to the availability of other external sources of funds such as traditional liquid funds and deposits (Loutskina, 2011). This implies that securitisation could reduce shocks to cost of funding which leads to lower bank risk.

2.4.1 Econometric Specification

We argue that securitisation activities impact both bank profitability and risk, and that this impact is transmitted through two channels; namely liquidity and cost of funding. To test this argument, we specify a structural model of the bank performance in which profitability, risk, liquidity, and cost of funding are jointly determined in equilibrium, while securitisation is exogenous. The model is specified as a system of equations as follows:

$$Y = B\,Y + \Gamma\,X + \zeta \tag{2.2}$$

where Y is a vector of the endogenous variables: profitability, risk, liquidity, and cost of funding. X is a vector of exogenous variables including securitisation. The coefficient matrix B represents the relationships among endogenous variables. The coefficient matrix Γ represents the relationships between endogenous and exogenous variables. ζ is vector of error terms. We estimate the model using two different measures for profitability: net interest margin and return on assets. We also use two different measures for bank risk: the ratio of risk-weighted assets to total assets and the ratio of loan loss allowance to total assets. Liquidity is measured as the ratio of cash and securities to total assets. Cost of funding is estimated as the ratio of interest expense to total assets. Finally, securitisation is estimated as the ratio of outstanding securitisation to total assets. For more details on data and variables description, see Section 2.2.2 and Table 2.1.

We estimate the system of structural equations specified in Equation 2.2 using the three-stage least square (3SLS) estimation method, which has several advantages over traditional ordinary least squares (OLS) estimation methods (Zellner and Theil, 1962). Given that in our model specification explanatory variables include some endogenous variables, error terms are expected to be correlated with the endogenous variables which violates the assumptions of ordinary least squares (OLS). Further, given that some dependent variables are the explanatory variables of other equations in the system, error terms among the equations are expected to be correlated. Three-stage least squares can correct for these biases given that it can be considered a combination of two-stage least squares (2SLS) and generalised least squares (GLS) (Greene, 2018). It is similar to 2SLS in that it uses an instrumental variable approach to provide consistent estimates and is similar to GLS in that it accounts for the correlation structure in the error terms across the equations.

To estimate a structural model, it is necessary for the model specification to satisfy the identification condition. To solve this identification problem in our model, we use some additional exogenous variables as instruments for endogenous variables in the model. We then estimate the model using the 3SLS estimation method in three stages. In the first stage, instrumented values are developed for all endogenous variables by running regressions of each endogenous variable on all exogenous variables in the system. This stage is important to producing consistent parameter estimates and is identical to the first step in 2SLS. In the second stage, the residuals from the 2SLS estimation are used to estimate the covariance matrix of each structural equation. This stage is necessary to obtain consistent estimates for the covariance matrices and correct for the correlation of disturbance among equations. Finally, the structural model is estimated using a GLS estimation in which the endogenous variables are replaced with their estimated values from the first stage of 3SLS and the covariance matrices from the second stage of 3SLS. We then use standard tests in the context of 3SLS to assess our model specification. First, in order to test for the weak instruments problem, we report the F-statistic and the p-value for each specification to test for the joint relevance of the instruments. We also report the R^2 for each structural equation and the system's McElroy R^2 (McElroy, 1977). Further, to assess the validity of instruments, we use the Hansen-Sargan test for overidentifying restrictions which tests whether the instruments, as a group, appear exogenous (Davidson et al., 2004). We use a vesion of the test that is robust to heteroskedasticity and autocorellation.

Our strategy of analyzing the role of securitisation in explaining the profitability-risk trade-off using a simultaneous equations modelling approach has a number of advantages. The main advantage is that it allows us to consider the potential problem of endogeneity given that the system of equations is estimated simultaneously. Another advantage of using this approach is that it allows us to explicitly consider the channels through which securitisation affects both bank profitability and risk, and identify the magnitude and direction of the impact. In addition, this approach enables us to decompose the effects of securitisation into direct and indirect effects which enables us to compare between these effects and examine how they differ between profitability and risk.

2.4.2 Empirical Results

Table 2.5 reports the results of estimating the structural model specified in Equation 2.2. Each column in the table shows the results of estimating a system of four equations for profitability, risk, liquidity, and cost of funding using securitisation as an exogenous variable. To assess the impact of securitisation on bank profitability and risk, we focus on the coefficient on securitisation in the profitability and risk equations. The results from different specifications show that securitisation has a significant and positive impact on both profitability and risk. These results hold through out the full sample period (2001Q2-2017Q4) and the two sample subperiods (2001Q2-2008Q4 and 2009Q4-2017Q4) and using different measures for profitability and risk.

Furthermore, given that all the variables included in the model are scaled by total assets, we can compare the effects of securitisation on profitability and risk straightforwardly. Indeed, this comparison yields some interesting findings. The magnitude of the effect of securitisation on bank risk is much larger compared

TABLE 2.5: **Securitisation and Profitability-Risk trade-off.**

This table shows the results of examining the role of securitisation in explaining the trade-off between profitability and risk of securitiser banks. Each model specification in columns 1 through 12 is a structural model of four equations for profitability, risk, liquidity, and cost of funding. All specifications are estimated using the three-stage least squares (3SLS) estimation method. The sample period includes quarterly data from 2001:Q2 through 2017:Q4. *Return_on_Assets* is the return on assets calculated as the ratio of net income to total assets. *Net_Interest_Margin* is the net interest margin calculated as the ratio of net interest income to total assets. *RWA* is the ratio of risk-weighted assets to total assets. *ALLOW* is the ratio of loan loss allowance to total assets. *Cost_of_Funding* is the ratio of interest expense to total assets. *Liquidity* is the ratio of cash and securities to total assets. *Securitisation* is the ratio of outstanding securitisation amounts to total assets. Standard errors in parentheses. *,**,*** denote statistical significance at the 10%, 5%, and 1% level respectively.

	2001-2017				2001-2008				2009-2017			
	Net_Interest_Margin		Return_on_Assets		Net_Interest_Margin		Return_on_Assets		Net_Interest_Margin		Return_on_Assets	
	RWA	ALLOW	RWA	ALLOW	RWA	ALLOW	RWA	ALLOW	RWA	ALLOW	RWA	ALLOW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Bank Profitability												
Liquidity_Ratio	-0.0122***	-0.0109***	-0.0013	-0.0010	-0.0158***	-0.0134***	-0.0032***	-0.0015	-0.0056***	-0.0083***	0.0012	0.0017
	(0.001)	(0.0011)	(0.0008)	(0.0008)	(0.0014)	(0.0014)	(0.001)	(0.001)	(0.0017)	(0.0015)	(0.0009)	(0.0011)
Cost_of_Funding	0.6361***	0.6303***	0.1957***	0.1931***	0.7513***	0.7376***	0.1998***	0.1861***	0.8743***	0.9963***	-0.1535***	-0.1754**
	(0.014)	(0.014)	(0.0104)	(0.0104)	(0.0189)	(0.019)	(0.0135)	(0.0135)	(0.0339)	(0.0339)	(0.0256)	(0.0756)
Securitisation	0.2311***	0.2323***	0.5711***	0.4214***	0.2441***	0.2463***	0.6891***	0.5401***	0.2153***	0.1869***	0.4254***	0.4470***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Constant	0.0178***	0.0175***	0.0034***	0.0034***	0.0141***	0.0136***	0.0039***	0.0037***	0.0168***	0.0172***	0.0049***	0.0046***
	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0004)	(0.0004)
Bank Risk												
Liquidity_Ratio	-0.4934***	-0.0014	-0.4821***	-0.0012	-0.5262***	-0.0014	-0.5461***	-0.0016	-0.4481***	-0.0057***	-0.4655***	-0.0061***
	(0.0131)	(0.0012)	(0.0130)	(0.0011)	(0.0196)	(0.0015)	(0.0205)	(0.0015)	(0.0161)	(0.0016)	(0.0151)	(0.0016)
Cost_of_Funding	3.9666***	0.1589***	3.9143***	0.1439***	3.0688***	0.1502***	3.0528***	0.1632***	1.5486***	0.6011***	1.4721***	0.7432***
	(0.1777)	(0.0155)	(0.1732)	(0.0145)	(0.2656)	(0.0202)	(0.3291)	(0.0213)	(0.3786)	(0.0382)	(0.3786)	(0.0382)
Securitisation	0.7723***	0.3901***	0.7724***	0.5549***	0.8117***	0.4855***	0.9117***	0.6432***	0.7257***	0.2804***	0.5257***	0.3869***
	(0.0026)	(0.0002)	(0.0026)	(0.0002)	(0.0036)	(0.0003)	(0.0036)	(0.0007)	(0.0038)	(0.0004)	(0.0038)	(0.0004)
Constant	0.8248***	0.0143***	0.8381***	0.0145***	0.8546***	0.0126***	0.8861***	0.0135***	0.8237***	0.0134***	0.6328***	0.0163***
	(0.0044)	(0.0004)	(0.0044)	(0.0003)	(0.0074)	(0.0006)	(0.0081)	(0.0008)	(0.0052)	(0.0005)	(0.0052)	(0.0005)
Liquidity												
Securitisation	-0.0141***	-0.0259***	-0.0191***	-0.0346**	-0.0121***	-0.0304***	-0.0221***	-0.0341***	-0.0095**	-0.0101**	-0.0122***	-0.0142***
	(0.0023)	(0.0024)	(0.0031)	(0.0029)	(0.0032)	(0.0036)	(0.0021)	(0.0019)	(0.0034)	(0.0038)	(0.0032)	(0.0036)
Constant	0.2498***	0.2514***	0.1654***	0.1893***	0.2416***	0.2445***	0.2484***	0.2475***	0.2575***	0.2502***	0.2485***	0.2453***
	(0.0011)	(0.0016)	(0.0009)	(0.0016)	(0.0025)	(0.0024)	(0.0022)	(0.0021)	(0.0021)	(0.0023)	(0.0026)	(0.0027)
Cost of Funding												
Securitisation	0.0134***	0.0172***	0.0144***	0.0189***	0.0054*	0.0133***	0.0114***	0.0163***	0.0242***	0.0271***	0.0164***	0.01759**
	(0.0021)	(0.0022)	(0.0021)	(0.0028)	(0.0031)	(0.0032)	(0.0032)	(0.0036)	(0.0014)	(0.0015)	(0.0019)	(0.0021)
Constant	0.0112***	0.0111***	0.0109***	0.0110***	0.0167***	0.0166***	0.0154***	0.0125***	0.0061***	0.0061***	0.0061***	0.0061***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
# of Observations	7592	7565	7592	7565	3806	3779	3806	3779	3786	3786	3786	3786
# of Instruments	4	4	4	4	4	4	4	4	4	4	4	4
McElroy System R^2	0.535	0.643	0.562	0.532	0.641	0.611	0.632	0.5821	0.432	0.371	0.476	0.429
Hansen-Sargan Test	0.671	0.715	0.276	0.202	0.481	0.283	0.492	0.373	0.112	0.1961	0.118	0.145
F Test [P-value]	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

to the magnitude of its effect on bank profitability. For example, a 1% increase in securitisation activities leads to 0.77% increase in risk-weighted assets compared to only 0.57% in return on assets for the full sample as shown in column 3. This finding holds for the two subperiods as well as shown in columns 7 and 11. Another interesting finding is that the effect of securitisation on profitability is larger when measured by return on assets compared to being measured by net interest margin. This is clear if we consider the two model specifications shown in columns 2 and 4 which are similar except for using return on assets in column 4 instead of net interest margin in column 2. The results show that a 1% increase in securitisation leads to 0.42% increase in return on assets compared to only 0.23% increase in net interest margin. This finding applies to risk as well. The effect of securitisation on risk is larger when measured by the ratio of risk-weighted assets compared to being measured by the allowance ratio. Considering the two similar specifications in column 1 and 2, a 1% increase in securitisation leads to 0.77% increase in risk-weighted assets compared to only 0.39% increase in the allowance ratio. Turning to comparing the effect of securitisation in the two subperiods, we notice a decline in the impact of securitisation on both profitability and risk in the period that followed the crisis. For example, comparing specifications 8 and 12, we find that a 1% increase in securitisation leads to a an increase of 0.54% in return on assets in the first subperiod compared to 0.45% in the second subperiod, and an increase of 0.64% in allowance ratio in the first subperiod compared to 0.38% in the second subperiod.

Overall, the results presented here contribute to explaining our earlier findings on the trade-off between bank profitability and risk for securitiser banks compared to banks that do not engage in securitisation activities as shown in Section 2.3. We show that securitisation improves bank profitability, but also increases its risk. This implies that for securitiser banks to increase their profitability, they have to bear more risks. The net impact on the bank will determine the contribution of securitisation to bank stability. We extend the analysis to study this point in Section 2.5.

2.4.3 Further Evidence

We extend the analysis presented above to focus on the role played by the two channels through which securitisation affects profitability and risk, namely liquidity and cost of funding. Given that we follow a simultaneous equations modelling approach to study the effects of securitisation on profitability and risk, we exploit an important advantage of this approach. It enables us to decompose the effects of securitisation into direct and indirect effects and to compare between these effects and to examine how they differ between profitability and risk. To this end, we rewrite the system of equations 2.2 in a matrix notation as follows:

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix} = \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} & \beta_{14} \\ \beta_{21} & \beta_{22} & \beta_{23} & \beta_{24} \\ \beta_{31} & \beta_{32} & \beta_{33} & \beta_{34} \\ \beta_{41} & \beta_{42} & \beta_{43} & \beta_{41} \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix} + \begin{bmatrix} \gamma_{11} \\ \gamma_{21} \\ \gamma_{31} \\ \gamma_{41} \end{bmatrix} \begin{bmatrix} x_1 \end{bmatrix} + \begin{bmatrix} \zeta_1 \\ \zeta_2 \\ \zeta_3 \\ \zeta_4 \end{bmatrix} \tag{2.3}$$

where y_1, y_2, y_3, and y_4 denote profitability, risk, liquidity, and cost of funding, respectively. x_1 denotes securitisation. A coefficient β_{ij} denotes the coefficient of an endogenous variable i on an endogenous variable j in the i^{th} equation. A coefficient γ_{ij} denotes the coefficient of an endogenous variable i on an exogenous variable j in the i^{th} equation. ζ_i denotes the error terms of the i^{th} equation. For ease of exposition, we present the system of equations with a single exogenous variable x_1 denoting our variable of interest; securitisation.

Further, we estimate the system of equations 2.3 using the three-stage least squares (3SLS) and use the estimated coefficients to calculate the direct, indirect and total effects of securitisation on profitability and risk. The direct effects on profitability and risk are simply equal to γ_{11} and γ_{21}, respectively. The indirect effect on profitability is calculated as the effect of securitisation on liquidity multiplied by the effect of liquidity on profitability plus the effect of securitisation on cost of funding multiplied by the effect of cost of funding on profitability ($\gamma_{31}\beta_{13} + \gamma_{41}\beta_{14}$). Similarly, the indirect effect on risk is calculated as the effect of securitisation on liquidity multiplied by the effect of liquidity on risk plus the the effect of securitisation on cost of funding multiplied by the effect of cost of funding on risk ($\gamma_{31}\beta_{23} + \gamma_{41}\beta_{24}$). The total effect is calculated as the summation of the direct effect and indirect effect.

The results of this analysis are reported in Table 2.6. Each column shows the indirect and total effects of securitisation on the profitability and risk measures shown at the top of the column based on estimating the system of equations 2.3 using these measures. We also report the results of a test of difference between the total effects on profitability and risk at the bottom of each column. In general, the results show that the indirect effect of securitisation on profitability is mostly positive except in specifications 11 and 12. Further, this indirect effect is larger in the case of net interest margin compared to return on assets whether in the full sample or in the two subperiods. In the case of risk, the indirect effect is positive in all specifications. This effect is larger in the case of the risk-weighted assets ratio compared to the allowance ratio whether in the full sample or in the two subperiods. Comparing the two subperiods, the results show that the magnitude of indirect effects on net interest margin has increased in the second subperiod (columns 9 and 10) compared to the first one (columns 5 and 6). The opposite is true with return on assets for which the indirect effect has declined in the second subperiod (columns 11 and 12) compared to the first one (columns 7 and 8). Also, the results show that the magnitude of indirect effects on the allowance ratio has increased in the second subperiod (columns 10 and 12) compared to the first one (columns 6 and 8). This is less clear for the risk-weighted assets ratio for which the indirect effect has increase in one specification (column 9 compared to 5) and decline in the other one (column 11 compared to 7). Turning to the total effects, we notice that it mostly follows the directions and dynamics shown by the direct effect (see Table 2.5). However, it is worth mentioning that the magnitude of total effects can deviate largely from direct effects due to the addition of indirect effects to reach at total effects. This can be highlighted if we consider column 12 in which the indirect effect is negative with profitability and positive with risk. When adding these indirect effects to direct effects to calculate total effects, we notice that the difference between total effects on profitability and on risk becomes less significant compared to the difference between direct effects on profitability and on risk. This is shown also by the result of the test of difference between total effects reported at the bottom of column 12 which is significant only at the 5% level. Overall, the results presented in this section provide a statistical justification for our modelling approach in which we use a simultaneous equations model to study the simultaneous impact of securitisation on both bank profitability and risk. Furthermore, the results highlight the importance of considering liquidity and cost of funding as two channels through which securitisation affects bank profitability and risk.

2.5 Securitisation, Bank Stability, and Systemic Risk

The results presented in Section 2.3 establish that, for banks that engage in securitisation activities, to increase profitability they should expect to bear more risk. In addition, we have extended the analysis in Section 2.4 to show how engagement in securitisation activities can explain this trade-off. In this section, we take the analysis one step further to examine the effects of securitisation on bank stability and systemic risk.

TABLE 2.6: **Decomposing the Effects of Securitisation on Profitability and Risk.**
This table shows the results of estimating the indirect and total effects of securitisation on profitability and risk. The results presented in each column from 1 through 12 are based on estimates from a structural model of four equations for profitability, risk, liquidity, and cost of funding. All specifications are estimated using the three-stage least squares (3SLS) estimation method. The sample period includes quarterly data from 2001:Q2 through 2017:Q4. *Return_on_Assets* is the return on assets calculated as the ratio of net income to total assets.*Net_Interest_Margin* is the net interest margin calculated as the ratio of net interest income to total assets. *RWA* is the ratio of risk-weighted assets to total assets. *ALLOW* is the ratio of loan loss allowance to total assets. *Profitability* and *Risk* represent the measures used for profitability and risk in each column, respectively. Standard errors in parentheses. *,**,*** denote statistical significance at the 10%, 5%, and 1% level respectively.

	2001-2017				2001-2008				2009-2017			
	Net_Interest_Margin		Return_on_Assets		Net_Interest_Margin		Return_on_Assets		Net_Interest_Margin		Return_on_Assets	
	RWA	ALLOW	RWA	ALLOW	RWA	ALLOW	RWA	ALLOW	RWA	ALLOW	RWA	ALLOW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Indirect Effects of Securitisation on:												
Profitability	0.0087***	0.0111***	0.0028***	0.0037***	0.0042***	0.0102***	0.0023***	0.0031***	0.0212***	0.0271***	-0.0025***	-0.0031***
	(0.0011)	(0.0012)	(0.0004)	(0.0004)	(0.0017)	(0.0018)	(0.0005)	(0.0006)	(0.0017)	(0.0017)	(0.0003)	(0.0003)
Risk	0.0601***	0.0028***	0.0656***	0.0028***	0.0229***	0.0020***	0.0469***	0.0027***	0.0417***	0.0163***	0.0298***	0.0131***
	(0.0135)	(0.0005)	(0.0135)	(0.0005)	(0.0172)	(0.0006)	(0.0172)	(0.0006)	(0.0173)	(0.0001)	(0.0173)	(0.0001)
Total Effects of Securitisation on:												
Profitability	0.2398***	0.2434***	0.5739***	0.4251***	0.2483***	0.2565***	0.6914***	0.5432***	0.2365***	0.2140***	0.4229***	0.4439***
	(0.0023)	(0.0025)	(0.0016)	(0.0016)	(0.0031)	(0.0033)	(0.0019)	(0.0002)	(0.0038)	(0.0038)	(0.0026)	(0.0026)
Risk	0.8324***	0.3929***	0.838***	0.5577***	0.8346***	0.4875***	0.9586***	0.6459***	0.7674***	0.2967***	0.5555***	0.4000***
	(0.0093)	(0.0024)	(0.0293)	(0.0024)	(0.0396)	(0.0029)	(0.0396)	(0.0029)	(0.0414)	(0.0039)	(0.0414)	(0.0039)
Test of Difference Between TotalEffects												
F Test [P-value]	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0112	0.0000	0.0401

2.5.1 Securitisation and Bank Stability

A large number of studies have shown that securitisation has had an adverse impact on banks financial soundness and the financial system in general in the run-up to the global financial crisis (DeMarzo, 2004; Gorton and Pennacchi, 1995; Chiesa, 2008; Parlour and Plantin, 2008). In particular, theoretical research shows that securitisation may not lead to the expected credit risk diversification. In addition, it could encourage banks to retain the most risky loans, undermine banks' screening and monitoring incentives, and could encourage banks to take more risk.

In contrast, empirical evidence on this issue before the 2008 financial crisis does not uniformly support these arguments. On one hand, some studies show that if banks are securitisation active they lend more to risky borrowers (Cebenoyan and Strahan, 2004; Franke and Krahnen, 2007), have less diversified portfolios and hold less capital (Casu et al., 2013), retain riskier loans (Calem and LaCour-Little, 2004), are aggressive in loan pricing (Kara et al., 2011), and carry high risk in general (Bannier and Hänsel, 2008; Affinito and Tagliaferri, 2010). On the other hand, there are studies showing that securitisation reduces banks insolvency risk (Jiangli et al., 2008), increases profitability (Cebenoyan and Strahan, 2004), provides liquidity (Loutskina and Strahan, 2009), and leads to greater supply of loans (Loutskina, 2011; Altunbas et al., 2009).

The literature on the effects of securitisation post the global financial crisis is also extensive. Most of these studies share the same arguments shown above on the negative consequences of securitisation on bank incentives. In particular, securitisation has been under scrutiny for fuelling credit growth by banks, lowering banks' credit standards and creating a false sense of diversification of risks. In other words, being one of the main causes of the financial crisis (Kara et al., 2011). Shin (2009) provides a theoretical framework showing how securitisation may impair financial stability if the imperative to expand bank balance sheets drives down lending standards. Others (Benmelech et al., 2012; Shivdasani and Wang, 2011; Casu et al., 2011) do not find a link between bank risk taking and securitisation.

Furthermore, the regulatory response post the crisis has aimed at addressing these flaws in the securitisation market. The efforts have been concentrated on promoting responsible securitisation through measures aiming to align interest between issuer banks and investors. Second, regulators have focused on reducing information asymmetries between the counterparties by improving transparency on underlying assets and the asset-backed structure and to support accurate pricing of credit risk. In this direction, some regulatory incentives from the European Central Bank (ECB) have introduced loan-level information requirements for ABSs if used as collateral in the Eurosystem's credit operations. Recent ECB initiatives also aim to identify qualifying securitisations, which through their simplicity, structural robustness and transparency, would enable investors to model risk with confidence and would provide originators with incentives to behave responsibly (Mersch, 2017). This can help reduce the negative impact of securitisation on bank stability.

Our strategy of analyzing the impact of securitisation on bank stability relies on adjusting our structural model of the bank performance presented above to account for risk-adjusted profitability as a function of securitisation activities, instead of considering profitability and risk separately. This model also accounts for the two channels through which securitisation affects both bank stability: liquidity and cost of funding. Based on this model, we construct and analyse the dynamics of a measure of the net effect of securitisation on bank stability.

2.5.1.1 Econometric Specifications

Our analysis has focused so far on the effects of securitisation on bank profitability and risk. Estimating these effects separately, however, is not sufficient to assess the impact of securitisation on bank stability. Therefore, there is a need for a measure that captures the impact on both profitability and risk simultaneously and in turn the impact on bank stability. To address this issue we construct a measure of risk-adjusted profitability for each bank as follows:

$$RAP_{i,t} = PROFIT_{i,t} - RISK_{i,t} \tag{2.4}$$

where $RAP_{i,t}$, $PROFIT_{i,t}$, and $RISK_{i,t}$ denote risk-adjusted profitability, profitability, and risk of bank i at time t. The rationale behind this measure is that securitisation activities can affect both profitability and risk either positively or negatively, but from a stability perspective it is the net effect that matters. In other words, if $RAP_{i,t}$ is positive (negative), the effect of securitisation on bank stability is said to be positive (negative). Further, to ensure consistency between profitability and risk measures, we calculate $RAP_{i,t}$ in two different methods. In the first, we use return on assets as a measure of profitability and the ratio of risk-weighted assets as a measure of risk in order to focus on the overall performance of the bank. In the second method, we use net interest margin as a measure of profitability and the allowance ratio as a measure of risk in order to focus on the loan portfolio of the bank. In addition, to ensure comparability all measures of profitability and risk are scaled by total assets.

Next, we adjust the model presented in Section 2.4 to specify a structural model of the bank stability in which risk-adjusted profitability, liquidity, and cost of funding are jointly determined in equilibrium, while securitisation is exogenous.

The model is specified as a system of equations as follows:

$$Y = B\ Y + \Gamma\ X + \zeta \tag{2.5}$$

where Y is a vector of the endogenous variables: risk-adjusted profitability, liquidity, and cost of funding. X is a vector of exogenous variables including securitisation. The coefficient matrix B represents the relationships among endogenous variables. The coefficient matrix Γ represents the relationships between endogenous and exogenous variables. ζ is a vector of error terms. We estimate the model using the risk-adjusted profitability measure as shown in Equation 2.4. Liquidity is measured as the ratio of cash and securities to total assets. Cost of funding is estimated as the ratio of interest expense to total assets. Finally, securitisation is estimated as the ratio of outstanding securitisation to total assets. For more details on data and variables description, see Section 2.2.2 and Table 2.1. In addition, we estimate the model using the three-stage least squares (3SLS) estimation method and report the standard specification and overidentification tests. For more details on the estimation method, see Section 2.4.

Furthermore, rewriting the system of equations 2.5 in a matrix notation yields:

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} \\ \beta_{21} & \beta_{22} & \beta_{23} \\ \beta_{31} & \beta_{32} & \beta_{33} \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} + \begin{bmatrix} \gamma_{11} \\ \gamma_{21} \\ \gamma_{31} \end{bmatrix} \begin{bmatrix} x_1 \end{bmatrix} + \begin{bmatrix} \zeta_1 \\ \zeta_2 \\ \zeta_3 \end{bmatrix} \tag{2.6}$$

where y_1, y_2, and y_3 denote risk-adjusted profitability, liquidity, and cost of funding, respectively. x_1 denotes securitisation. A coefficient β_{ij} denotes the coefficient of an endogenous variable i on an endogenous variable j in the i^{th} equation. A coefficient γ_{ij} denotes the coefficient of an endogenous variable i on an exogenous variable j in the i^{th} equation. ζ_i denotes the error terms of the i^{th} equation. For ease of exposition, we present the system of equations with a single exogenous variable x_1 denoting our variable of interest; securitisation.

Finally, we use the estimated coefficients from the system of equations 2.6 to calculate the direct, indirect and total effects of securitisation on risk-adjusted profitability as shown in Section 2.4. We then construct a measure of bank stability which is defined as the sensitivity of the bank risk-adjusted profitability to changes in securitisation activities. This measure can be estimated using the estimated direct and indirect effects of securitisation on risk-adjusted profitability as follows:

$$S\text{–}score = \frac{d\ RAP}{d\ SEC} = \gamma_{11} + \gamma_{21}\beta_{12} + \gamma_{31}\beta_{13} \tag{2.7}$$

where $S\text{–}score$ is a measure of the impact of securitisation on bank stability. $\frac{d\ RAP}{d\ SEC}$ is the total derivative of risk-adjusted profitability with respect to securitisation. The terms γ_{11} and $\gamma_{21}\beta_{12} + \gamma_{31}\beta_{13}$ represent the direct and indirect effects of securitisation on risk-adjusted profitability, respectively.

2.5.1.2 Empirical Results

The results of estimating the structural model specified in Equation 2.5 are reported in Table 2.7. Each column in the table shows the results of estimating a system of three equations for risk-adjusted profitability, liquidity, and cost of funding using securitisation as an exogenous variable. To assess the impact of securitisation on bank stability, we focus on the coefficient on securitisation in the risk-adjusted profitability equation. The results from different specifications show that securitisation significantly and negatively affects bank stability. These results hold when using different measures for risk-adjusted profitability and through out the full sample period (2001Q2-2017Q4) and the two sample subperiods (2001Q2-2008Q4 and 2009Q4-2017Q4). Nevertheless, the magnitude of this decline depends on how risk-adjusted profitability is measured. In particular, the effect is larger when using return on assets and risk-weighted assets ratio to calculate risk-adjusted profitability (-0.16%, -0.24%, -0.09% in columns 1, 3, and 5) compared to using net interest margin and the allowance ratio (-0.20%, -0.22%, -0.10% in columns 2, 4, and 6). This implies that the impact is larger when using measures of overall bank profitability and risk as compared to focusing on the loans portfolio, which is in line with our earlier results on the effect of securitisation on profitability and risk. Turning to comparing the effect of securitisation in the two subperiods, we can notice an interesting finding. There is a decline in the effects of securitisation on risk-adjusted profitability in the period that followed the crisis. For example, comparing specifications 3 and 5, we find that a 1% increase in securitisation leads to a decline of 0.23% in risk-adjusted profitability in the first subperiod compared to 0.09% in the second subperiod.

Further, we report the results of examining the effects of securitisation on bank stability in Table 2.8. Each column shows the direct and indirect effects of securitisation on risk-adjusted profitability based on estimating the system of equations 2.5. In addition, for each specification, we report *S–score* which is our proposed measure of the impact of securitisation on bank stability. Comparing the results across specifications yields some interesting findings. Regarding the indirect effect of securitisation on stability, the results show that it is positive when focusing on the loans portfolio (columns 1, 3, and 5), but turns negative when focusing on the overall performance of the bank (columns 2, 4, and 6). This contradiction is due to the opposite effect of liquidity and cost of funding on risk-adjusted profitability when measured at the loans portfolio level as compared to the overall balance sheet level (see Table 2.7). In addition, this indirect effect is larger in the case of measuring risk-adjusted profitability at the loans portfolio level as compared to the overall balance sheet level. Turning to the *S–score* measure, we notice that it is negative across specifications. For instance, in the full sample, a 1% increase in securitisation is associated with an *S–score* of -0.14% at the loans portfolio level and -0.25% at the overall balance sheet level. This

Implies that the net impact of securitisation on bank stability is negative. In addition, comparing the *S–score* measure between the two subperiods shows that its magnitude is larger in the first subperiod (columns 3 and 4) compared to the second subperiod (columns 5 and 6).

Overall, the results presented here extend our earlier findings on the positive effect of securitisation on both bank profitability and risk for securitiser banks compared to banks that do not engage in securitisation activities as shown in Section 2.4. We have taken the analysis one step further to examine the effects of securitisation on bank stability. Our results show that securitisation activities are destabilising. The net impact of securitisation on banks is generally negative when we measure the bank performance based on risk-adjusted profitability measures. This impact is negative whether at the loans portfolio level or the overall balance sheet level. This destabilising effect is more significant in the period that led to the global financial crisis in 2008 compared to the period that followed the crisis. Nevertheless, our analysis is silent so far on why these results are different before and after the global financial crisis. In Section 2.6, we put forward an explanation for this difference.

2.5.1.3 Further Evidence

To further highlight the dynamics of *S–score* over time, we estimate the structural model specified in Equation 2.5 using a twelve-quarters rolling-window of data over the full sample period from 2001Q2 through 2017Q4. We then calculate *S–score* using the estimated coefficients as shown by Equation 2.6 for each quarter from 2004Q2 through 2017Q4. We estimate *S–score* in two ways. The first is at the loan portfolio level using net interest margin as a measure of bank profitability and the allowance ratio as a measure of the riskiness of the loan portfolio. The second is at the overall balance sheet level using return on assets

TABLE 2.7: **Securitisation and Risk-Adjusted Profitability.**
This table shows the results of examining the effects of securitisation on Risk-Adjusted Profitability. Each model specification in columns 1 through 6 is a structural model of three equations for risk-adjusted profitability, liquidity, and cost of funding. All specifications are estimated using the three-stage least squares (3SLS) estimation method. The sample period includes quarterly data from 2001:Q2 through 2017:Q4. *NIM–ALLOW* is the risk-adjusted profitability calculated using net interest margin to measure profitability and the allowance ratio to measure risk. *ROA–RWA* is the risk-adjusted profitability calculated using return on assets to measure profitability and the risk-weighted assets ratio to measure risk. *Liquidity* is the ratio of cash and securities to total assets. *Cost_of_Funding* is the ratio of interest expense to total assets. *Securitisation* is the ratio of outstanding securitisation amounts to total assets. Standard errors in parentheses. *,**,*** denote statistical significance at the 10%, 5%, and 1% level respectively.

	Risk-Adjusted Profitability					
	2001Q2-2017Q4		2001Q2-2008Q4		2009Q1-2017Q4	
	NIM–ALLOW	ROA–RWA	NIM–ALLOW	ROA–RWA	NIM–ALLOW	ROA–RWA
	(1)	(2)	(3)	(4)	(5)	(6)
Risk-Adjusted Profitability						
Liquidity	-0.0125***	0.4935***	-0.0121***	0.5249***	-0.0141***	0.4503***
	(0.0013)	(0.1304)	(0.0017)	(0.1924)	(0.0019)	(0.1681)
Cost_of_Funding	0.4489***	-3.6872***	0.5504***	-2.7556***	0.3914***	-1.7177***
	(0.0169)	(0.2726)	(0.0225)	(0.2582)	(0.0260)	(0.3772)
Securitisation	-0.1578***	-0.2013***	-0.2392***	-0.2226***	-0.0935**	-0.1003*
	(0.0271)	(0.0256)	(0.0323)	(0.0348)	(0.0467)	(0.0574)
Constant	-0.3543***	-0.8224***	-0.3832**	-0.8526***	-0.4132***	-0.8189***
	(0.0632)	(0.0838)	(0.0641)	(0.0724)	(0.0643)	(0.0821)
Liquidity						
Securitisation	-0.0254***	-0.0136***	-0.0292***	-0.0115***	-0.0241***	-0.0141***
	(0.0023)	(0.0022)	(0.0031)	(0.0029)	(0.0038)	(0.0028)
Constant	0.2511***	0.2495***	0.2541***	0.2413***	0.2575***	0.2465***
	(0.0161)	(0.0163)	(0.0024)	(0.0026)	(0.0023)	(0.0027)
Cost of Funding						
Securitisation	0.0192***	0.0141***	0.0142***	0.0132***	0.0243*	0.0171***
	(0.0018)	(0.0017)	(0.0023)	(0.0021)	(0.0016)	(0.0014)
Constant	0.0114***	0.0115***	0.0171***	0.0148***	0.0161**	0.0152**
	(0.0012)	(0.0014)	(0.0021)	(0.0018)	(0.0071)	(0.0062)
# of Observations	7708	7736	3922	3950	3786	3786
# of Instruments	4	4	4	4	4	4
McElroy System R^2	0.538	0.655	0.573	0.725	0.453	0.517
Hansen-Sargan Test	0.345	0.421	0.525	0.432	0.124	0.234
F Test [P-value]	0.000	0.000	0.000	0.000	0.000	0.000

TABLE 2.8: **Securitisation and Bank Stability.**
This table shows the results of estimating the direct, and indirect effects of securitisation on risk-adjusted profitability and constructing *S–score* as a measure of the impact of securitisation on bank stability. The results presented in each column from 1 through 6 are based on estimates from a structural model of three equations for risk-adjusted profitability, liquidity, and cost of funding. All specifications are estimated using the three-stage least squares (3SLS) estimation method. The sample period includes quarterly data from 2001:Q2 through 2017:Q4. *NIM–ALLOW* is the risk-adjusted profitability calculated using net interest margin to measure profitability and the allowance ratio to measure risk. *ROA–RWA* is the risk-adjusted profitability calculated using return on assets to measure profitability and the risk-weighted assets ratio to measure risk. *S–score* measures the impact of securitisation on bank stability. Standard errors in parentheses. *,**,*** denote statistical significance at the 10%, 5%, and 1% level respectively.

	2001-2017		2001-2008		2009-2017	
	NIM–ALLOW	ROA–RWA	NIM–ALLOW	ROA–RWA	NIM–ALLOW	ROA–RWA
	(1)	(2)	(3)	(4)	(5)	(6)
Bank Stability						
Direct Effect	-0.1578***	-0.2013***	-0.2392***	-0.2226***	-0.0935**	-0.1003*
	(0.0018)	(0.0017)	(0.0023)	(0.0021)	(0.0016)	(0.0014)
Indirect Effect	0.0089***	-0.0587***	0.0082***	-0.0424***	0.0099***	-0.0357***
	(0.0010)	(0.0130)	(0.0014)	(0.0164)	(0.0009)	(0.0174)
S–score	-0.1489***	-0.2593***	-0.231***	-0.2646***	-0.0836*	-0.1353**
	(0.0281)	(0.0285)	(0.0351)	(0.0383)	(0.0501)	(0.0581)

as a measure of profitability and the ratio of risk-weighted assets as a measure of the riskiness of total assets.

The results of this exercise are shown in Figure 2.3. Panels (A) and (B) show the estimated *S–score* at the loan portfolio and balance sheet levels, respectively. Interestingly, the dynamics shown in both panels are very similar. The *S–score* is negative during most of the quarters. Both panels also show that the destabilising impact of securitisation is more severe in the run-up to the global financial crisis, where it bottoms out in 2010Q4. However, it is worth noting that the three-years window of data used for estimation implies that the lowest values for the *S–score* are actually based on data mostly from the period of the global financial crisis. Following the crisis, the destabilising effect seems to have declined. Nevertheless, none of the two estimates of *S–score* show any significant positive effects of securitisation on bank stability, even in the aftermath of the global financial

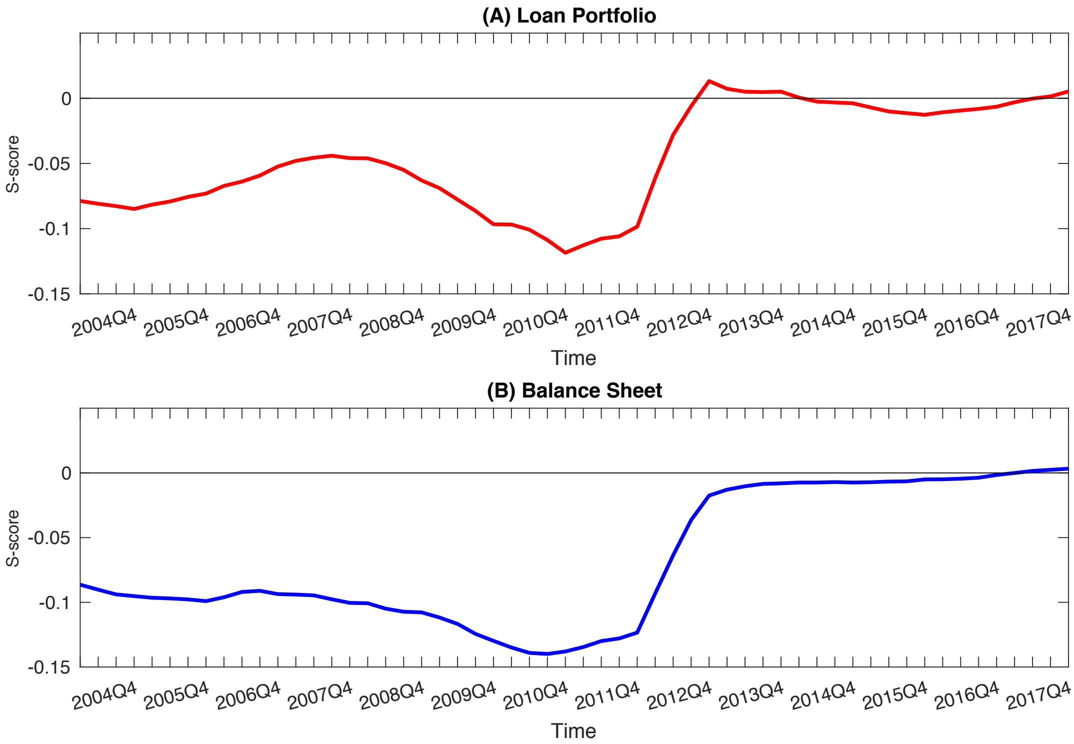

FIGURE 2.3: *S–score*: A Measure of the Impact of Securitisation on Bank Stability. Panel (A) shows estimated *S–score* at the loan portfolio level. Panel (B) shows estimated *S–score* at the overall balance sheet level.

crisis.

2.5.2 Securitisation and Systemic Risk

Our strategy of analyzing the impact of securitisation on systemic risk at the banking system level relies on evaluating the commonality among banks returns from securitisation activities as an indicator of interconnectedness and systemic risk.

2.5.2.1 Econometric Specifications

Our analysis has focused so far on the effects of securitisation at the bank level. Estimating these effects, however, is not sufficient to gauge the systemic effects of securitisation. Therefore, to address this issue, we measure the commonality among the returns from securitisation activities of banks as an indicator of the systemic effects of securitisation activities. Our main argument here is that increased commonality among the asset returns of banks is an indicator of increased systemic risk (Caccioli et al., 2015*a*; Battiston et al., 2012*a*). To identify this commonality, we use the measure suggested by (Billio et al., 2012) based on principal components analysis (PCA) to capture the changes in commonality among the returns from securitisation activities of banks. PCA is a technique in which the asset returns of financial institutions can be decomposed into orthogonal components of decreasing explanatory power (Jackson, 2005).

Formally, let R^i be the return from securitisation of bank i, $i = 1, ..., N$, let $E[R^i] = \mu_i$, and let $Var[R^i] = \sigma_i^2$. Further, let the system's aggregate return from securitisation be $R^S = \sum_i R^i$, and let $Var[R^S] = \sigma_S^2$. It then follows that:

$$\sigma_S^2 = \sum_{i=1}^{N} \sum_{j=1}^{N} \sigma_i \sigma_j E[z_i z_j] \tag{2.8}$$

where z is standardised return from securitisation. The PCA decomposes the variance-covariance matrix of returns from securitisation of the N banks into an orthonormal matrix of loadings $L = \{L_{ik}\}$ which represents the eigenvectors of the correlation matrix of returns, and a diagonal matrix $\Lambda = \{\Lambda_k\}$ which represents eigenvalues. Equation 2.8 can then be written as:

$$\sigma_S^2 = \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sigma_i \sigma_j l_{ik} l_{jk} \lambda_k \tag{2.9}$$

where λ_k denotes principal components, $k = 1, ..., N$.

It is expected that the first few components will explain most of the volatility in the system. In addition, they capture a larger portion of the total volatility when returns tend to move together which is often associated with crisis periods. Therefore, we analyse the systemic effects of securitisation by examining the portion of volatility in return from securitisation activities that is explained by the first few principal components. An increase in this portion is indicative of increased commonality in returns from securitisation activities and increased interconnectedness among banks, and accordingly higher systemic risk.

2.5.2.2 Empirical Results

We apply the PCA using data on net securitisation income of individual banks over the period 2001Q2-2017Q4. We use rolling windows of twelve quarters of data to construct a time series of principal components and cumulative risk fractions. The results of this analysis are shown in Figure 2.4 and summary statistics are reported in Table 2.9. The time series graph of principal components shows that the first six principal components (PC1, PC2-3, and PC4-6) capture the majority of variation in net securitisation income over the full sample period. Nevertheless, the relative importance of these groups of PCs varies considerably. In particular, Figure 2.4 shows that PC1 is very dynamic, capturing from 27% to 42% of variation in net securitisation income. The PC1 was already high from the beginning of the sample period and started to increase from 2005Q4 in the run-up to the global financial crisis, peaking at 42% in 2008Q4. It then declined in the aftermath of the crisis bottoming out at 27% in 2017Q1. On average, the PC1 explains 36% of the variation in net securitisation income in the period that preceded the global financial crisis compared to 31% in the period that followed the crisis. This implies that securitisation activities have contributed to increasing interconnectedness among banks in the run-up to the global financial crisis, hence increasing systemic risk in the banking system.

In addition, Table 2.9 reports the principal components and cumulative risk fractions for five selected time periods: 2004Q1-2006Q4, 2006Q1-2008Q4, 2009Q1-2011Q4, 20012Q1-2014Q4, and 2014Q1-2017Q4. As shown by the Cumulative Risk Fractions, the first six principal components capture 92%, 93%, 88%, 89%,

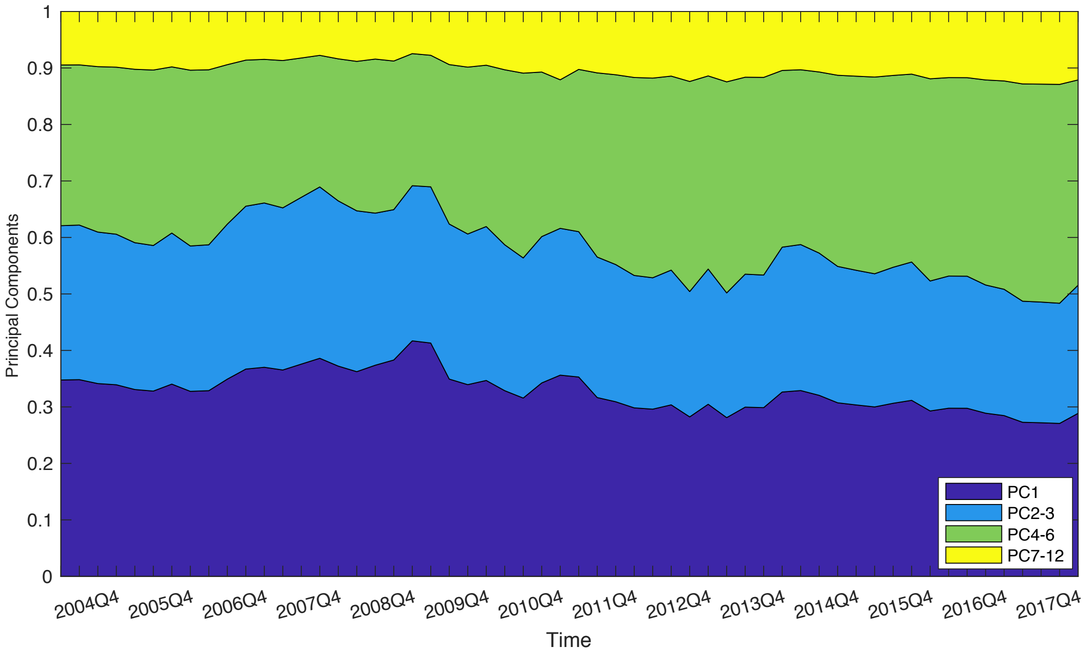

FIGURE 2.4: **Results of Principal Components Analysis**
This figure presents the principal components grouped into four groups including PC1, PC2-3, PC4-6, and PC-12. Estimates are based on a 12-quarters rolling-window principal components analysis of the quarterly standardised net securitisation income of individual banks over the sample period 2001Q2-2017Q4.

and 88% of the variability in net securitisation income among banks in these five time periods, respectively. On average, the first six (three) principal components explain 90% (59%) of this variability. Further, the first principal component explains 34% of the variability in net securitisation income, on average. Interestingly, the first principal component explains 42% in the period from 2006Q1 through 2008Q1, which is the highest compared to all other time periods. Overall, comparing these five periods confirms our results above that securitisation activities have contributed more to the increasing interconnectedness among banks in the run-up to the global financial crisis and increased systemic risk in the banking system.

TABLE 2.9: **Results of Principal Components Analysis**
This table reports summary statistics for Principal Components including PC1, PC2-3, PC4-6, and Cumulative Risk Fractions including PC1, PC1-3, PC1-6. Statistics are based on the quarterly standardised net securitisation income of individual banks over the sample period 2001Q2-2017Q4. Minimum, mean and maximum values are reported for three sample periods: 2001Q1-2017Q4, 2001Q1-2008Q4, and 2009Q1-2017Q4. Principal components and cumulative risk fractions are reported for five selected time periods: 2004Q1-2006Q4, 2006Q1-2008Q4, 2009Q1-2011Q4, 20012Q1-2014Q4, and 2014Q1-2017Q4.

		Principal Components			Cumulative Risk Fraction		
		PC1	PC2-3	PC4-6	PC1	PC1-3	PC1-6
Main Sample Periods							
2004Q1-2017Q4							
	Min	27%	21%	23%	27%	48%	87%
	Mean	33%	25%	31%	33%	58%	89%
	Max	42%	30%	39%	42%	69%	93%
2004Q1-2008Q4							
	Min	33%	26%	23%	33%	58%	90%
	Mean	36%	28%	28%	36%	63%	91%
	Max	42%	30%	31%	42%	69%	93%
2009Q1-2017Q4							
	Min	27%	21%	23%	27%	48%	87%
	Mean	31%	24%	33%	31%	55%	89%
	Max	41%	28%	39%	41%	69%	92%
Selected Time Periods							
2004Q1-2006Q4		37%	29%	25%	37%	66%	92%
2006Q1-2008Q4		42%	27%	23%	42%	69%	93%
2009Q1-2011Q4		30%	23%	35%	30%	53%	88%
2012Q1-2014Q4		30%	24%	34%	30%	54%	89%
2015Q1-2017Q4		29%	23%	36%	29%	52%	88%

2.6 The Role of Monetary Policy

The results presented in Section 2.4 show that securitisation activities improve bank profitability, but also increase its risk. Further investigation in Section 2.5 shows that securitisation activities have negative impact on bank stability and systemic risk. An interesting finding in both cases is that the effects of securitisation on either profitability, risk, stability, or systemic risk differ significantly between the period from 2001Q2 through 2008Q1 which preceded the global financial crisis, compared to the period from 2009Q1 through 2017Q4 which followed the crisis. So far, our analysis has been silent on why these results are different.

In this section, we put forward an explanation for this difference.

We argue that the decline in monetary policy short-term interest rates has mitigated the destabilising impact of securitisation on banks following the onset of the global financial crisis. This can be justified on the basis that a decline in monetary policy rates would encourage banks to rely more on traditional funding sources compared to securitisation. Banks would then be selective regarding which loans to grant, and which loans to securitise. This would eventually reduce risk taking by banks in their securitisation activities and reduce its destabilising effect. We put this argument to test using an identification strategy centred around an exogenous monetary policy shock following the global financial crisis. Specifically, we evaluate whether the destabilising impact of securitisation has changed around the dramatic decline in short-term interest rates following the onset of the global financial crisis, that might have affected bank incentives to securitise loans.

2.6.1 Econometric Specifications

As discussed above, we are interested in studying the role of short term interest rates in mitigating or worsening the impact of securitisation activities on bank stability. Therefore, to analyse how the net impact of securitisation activities depends on monetary policy interest rates, we follow Duchin et al. (2010) and employ a difference-in-differences (DID) approach with a continuous treatment variable (monetary policy interest rates). More specifically, we compare the change in *S–score* of banks before and after the decline in federal funds rate following the onset of the global financial crisis. To this end, we estimate the following regression specification:

$$\Delta S\text{–}score_{i,t} = \alpha_i + \beta_1\, iPOST + \beta_2\, iPOST \times FED_t + \gamma\, \mathbf{X}_{i,t} + \theta_t + \varepsilon_{i,t} \quad (2.10)$$

where $\Delta S\text{–}score$ denotes the change in the impact of securitisation on bank stability, $iPOST$ is an indicator variable equal to one for every quarter after and including 2009Q1, and zero before that, FED is the end of quarter effective federal funds rate, $\mathbf{X}$ is a vector of control variables, θ is a time-specific effect, and ε is the error term. In this specification, we specifically focus on the coefficient β_2 which captures the decrease in the destabilising effect of securitisation in the low interest rate era. It is expected to be positive to reflect the improvement in *S–score* with the decline in fed funds rate. We estimate *S–score* for individual banks based on the structural model specified in Equation 2.5 and based on a twelve-quarters rolling-window of data over the period from 2001Q2 through 20017Q4.

To estimate our difference-in-differences model, we use a window of eight years of data from 2005Q1 through 2012Q4, surrounding the severe decline in federal funds rates at the fourth quarter of 2008 following the onset of the global financial crisis. In addition, we use a bank-specific fixed effects estimation method with time dummies included to control for time-fixed effects and heteroskedasticity-consistent standard errors clustered at the bank level following (Bertrand et al., 2004).

2.6.2 Empirical Results

Table 2.10 presents estimates of the difference-in-differences specification described above. We use two measures for individual banks *S–score*. The first is related to the loan portfolio and estimated based on net interest margin and the allowance ratio, and the second is related to the overall balance sheet of the bank and estimated based on return on assets and the ratio of risk-weighted assets. The coefficients of interest are the coefficient on the exogenous monetary policy shock dummy and the coefficient on the interaction between this dummy and federal funds rate. The positive value of these coefficients indicate a decline in the destabilising effect of securitisation activities during the low interest rate era.

Column 1 of Table 2.10 establishes the main pattern in the data. It shows that *S–score* measured at loan portfolio level has improved by 2.88% by the average bank in the low interest rate period. The magnitude of this improvement is supported by our previous estimates of *S–score* at the banking system level as shown in Section 2.5. Column 2 shows that this improvement is substantially greater when considering the impact of the exogenous monetary policy shock. The coefficient estimate implies that, on average, *S–score* has improved by 3.24%, which increases to 5.23% when considering the decline in federal funds rate. Further, controlling for bank heterogeneity in column 3 shows that the estimated coefficients on the monetary policy dummy variable and its interaction with federal funds rate remain statistically significant and further increase in magnitude.

Turning to the impact of monetary policy change on *S–score* measured at the overall balance sheet level, we notice similar pattern to that described above at the loan portfolio level. Column 4 of Table 2.10 shows that *S–score* measured at the balance sheet level has improved by 1.37% by the average bank in the low interest rate period. The magnitude of this improvement is supported by our previous estimates of *S–score* at the banking system level as shown in Section 2.5. Column 5 shows that this improvement is substantially greater when considering the impact of the exogenous monetary policy shock. The coefficient estimate implies that, on average, *S–score* has improved by 1.52%, which increases to 3.22% when considering the decline in federal funds rate. Further, controlling for bank heterogeneity in column 6 shows that the estimated coefficients on the monetary policy dummy variable and its interaction with federal funds rate remain statistically significant and further increase in magnitude.

TABLE 2.10: **Results on the Role of Monetary Policy I.**
This table reports the results from a difference-in-differences analysis of the role of monetary policy in mitigating the impact of securitisation on bank stability. All specifications 1 through 6 are fixed effects regressions. The sample period includes an eight-year window of quarterly data from 2005Q1 through 2012Q4. $\Delta S\text{–}score$ is the change in the impact of securitisation on bank stability. *NIM–ALLOW* indicates that *S–score* is estimated using net interest margin as a measure profitability and the allowance ratio as a measure risk. *ROA–RWA* indicates that *S–score* is estimated using return on assets to measure profitability and the risk-weighted assets ratio to measure risk. *iPOST* is an indicator variable for the low interest rate period that is equal to 1 in quarters after and including 2009Q1, and 0 otherwise. *FED* is end-of-quarter effective federal funds rate. *Size* is the natural logarithm of total assets. *Equity* is the ratio of Tier 1 risk-based capital ratio to total assets. Standard errors in parentheses. *,**,*** denote statistical significance at the 10%, 5%, and 1% level respectively.

	$\Delta S\text{–}score$					
	NIM–ALLOW			ROA–RWA		
	(1)	(2)	(3)	(4)	(5)	(6)
iPOST	2.883***	3.241***	3.532***	1.371***	1.515***	1.539***
	(0.732)	(0.864)	(0.917)	(0.045)	(0.049)	(0.061)
iPOST×FED		5.234***	5.554***		3.217***	3.456**
		(1.345)	(1.427)		(1.141)	(1.262)
Size			-1.134*			-2.181**
			(0.625)			(1.104)
Equity			8.261**			5.766**
			(4.418)			(2.745)
Constant	-2.468***	-4.189***	-9.311***	-0.498***	-0.311***	-14.875***
	0.701	0.946	3.843	0.132	0.112	2.765
# of Observations	3,338	3,338	3,338	3,339	3,339	3,339
Adjusted R^2	0.072	0.094	0.132	0.083	0.103	0.121
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Overall, the results support the mitigating role of low interest rates on the net impact of securitisation on bank stability as measured by *S–score*. It is also worth noting that the magnitude of improvement in the this destabilising impact is higher when measured at the loan portfolio level compared to being measured at the overall balance sheet level. This implies that mitigating effects of low interest rates has been higher at the loan portfolio level, which is supported by our earlier findings shown in Section 2.5.

2.6.3 Further Evidence

In response to the global financial crisis, several regulatory initiatives were enacted which brought about several structural changes into the banking industry and securitisation markets. Examples include the Housing and Economic Recovery Act of 2008, the Dodd-Frank Act of 2010, as well as the unconventionally low monetary policy short-term interest rates. This implies that the effect of monetary policy interest rates could be commingled with the effects of other policy initiatives that coincided with monetary policy decline following the global financial crisis. Therefore, to check the robustness of our results from the difference-in-differences analysis presented above, we conduct an additional test in which we examine the impact of monetary policy interest rates on the return from and riskiness of securitisation activities. This approach has the added benefit of explicitly considering the direct impact of monetary policy interest rates on the profitability and riskiness of securitisation activities, which translates into the effects of securitisation on bank stability.

We measure return from securitisation activities by the ratio of net securitisation income to total assets $NSIOA$. Both values are obtained from call reports of individual banks. Whereas, riskiness of securitisation is measured using an adjusted version of the Altman *Z–score* (Altman, 1968) calculated based on securitisation activities as follows:

$$Z\text{−}score_{i,t} = \frac{NSIOA_{i,t} + Equity_{i,t}}{\sigma_{NSIOA_{i,t}}}$$

where $Z\text{−}score$, $NSIOA$, $Equity$, and σ_{NSIOA} are the adjusted $Z\text{−}score$, the ratio of net securitisation income to total assets, the ratio of equity capital to total assets, and the standard deviation of net securitisation income, respectively. Indices i and t denote banks and time, respectively. We estimate $\sigma_{NSIOA_{i,t}}$ based on a twelve-quarters rolling-window of the ratio of net securitisation income to total assets.

Next, we estimate the following regression specification for return from securitisation activities:

$$\Delta NSIOA_{i,t} = \alpha_i + \beta_1 \, \Delta NSIOA_{i,t-1} + \beta_2 \, FED_{t-1} + \gamma \, \mathbf{X}_{i,t-1} + \theta_t + \varepsilon_{i,t} \quad \textbf{(2.11)}$$

and the following regression specification for riskiness of securitisation activities:

$$\Delta Z{-}score_{i,t} = \alpha_i + \beta_1 \, \Delta Z{-}score_{i,t-1} + \beta_2 \, FED_{t-1} + \gamma \, \mathbf{X}_{i,t-1} + \theta_t + \varepsilon_{i,t} \quad \textbf{(2.12)}$$

where FED is federal funds rate, $\mathbf{X}_{i,t}$ is a vector of control variables, θ_t is time-specific fixed effect, and $\varepsilon_{i,t}$ is an error term. In addition, we estimate these specifications using the system generalised method of moments (System-GMM) estimation method and report the standard specification and overidentification tests. For more details on the estimation method, see Section 2.3. The data sample used to estimate these specification is quarterly data from 2004Q2 through 2017Q4.

The results from estimating specifications 2.11 and 2.12 are presented in Table 2.11, which provides estimates over three sample periods: 2004Q2-2017Q4, 2004Q2-2008Q4, 2009Q1-2017Q4. Columns 1, 2, and 3 show the results of evaluating the impact of monetary policy interest rates on the return from securitisation activities. The coefficient on fed funds rate is positive and significant throughout the sample period, which matches our expectations. Column 1 shows that a 100 basis point increase in fed funds rate leads to an increase in the ratio of net securitisation income of 2.62%, on average. Interestingly, the magnitude of this impact is different when comparing between the two subperiods 2004Q-2008Q4 and 2009Q1-2017Q4. On average, a 100 basis point increase in fed funds

TABLE 2.11: **Results on the Role of Monetary Policy II.**
This table reports the results of evaluating the impact of monetary policy interest rates on the return and riskiness of securitisation activities. Model specifications in columns 1 through 6 are estimated using the System-GMM estimation method. The sample includes quarterly data and estimates are provided for the full sample; 2004Q2-2017Q4 and for two subsamples: 2004Q2-2008Q4, and 2009Q1-2017Q4. $\Delta NSIOA$ is the change in the ratio of net securitisation income to total assets. Δ *Z-score* is the change in the adjusted Z-score estimated based on the ratio of net securitisation income to total assets of individual banks. *FED* is the end-of-quarter effective federal funds rate. *Size* is the natural logarithm of total assets. *Equity* is the ratio of Tier 1 risk-based capital ratio to total assets. *Trading_Assets* is the ratio of trading assets to total assets. *Deposits* is the ratio of bank deposits to total assets. Standard errors in parentheses. *,**,*** denote statistical significance at the 10%, 5%, and 1% level respectively.

	Δ NSIOA			Δ Z-score		
	2004-2017	2004-2008	2009-2017	2004-2017	2004-2008	2009-2017
	(1)	(2)	(3)	(4)	(5)	(6)
Δ NSIOA_{t-1}	0.110***	0.124***	0.069***			
	(0.0027)	(0.0021)	(0.0073)			
Δ Z-score_{t-1}				0.154***	0.189***	0.155***
				(0.0341)	(0.0452)	(0.0118)
FED_{t-1}	2.618***	3.621***	1.471**	1.192**	1.929***	-0.861**
	(0.0019)	(0.0074)	(0.7226)	(0.5871)	(0.6301)	(0.416)
Size_{t-1}	0.479*	1.226*	0.109	0.038***	0.021***	0.006
	(0.2714)	(0.6531)	(0.1761)	(0.0053)	(0.0013)	(0.0256)
Equity_{t-1}	21.75***	23.49***	12.130***	-0.492***	-0.453***	-0.249**
	(0.0151)	(0.1951)	(0.135)	(0.0180)	(0.0296)	(0.1110)
$\text{Trading\_Assets}_{t-1}$	-3.769**	-6.20***	-5.88**	0.456	1.873*	3.118**
	(1.7660)	(3.212)	(2.456)	(1.0689)	(1.1051)	(1.516)
Deposits_{t-1}	8.146***	5.68*	1.353***	-0.045***	-0.120***	-0.038
	(4.0079)	(3.3814)	(0.0716)	(0.0065)	(0.0069)	(0.0478)
# of Observations	1,743	1,231	512	756	448	308
# of Banks	113	96	46	52	43	30
# of Instruments	20	20	20	20	20	20
AR(1)	0.147	0.150	0.008	0.049	0.006	0.111
AR(2)	0.455	0.424	0.431	0.871	0.143	0.876
Hansen Test	0.582	0.734	0.606	0.307	0.773	0.171

rate leads to an increase in the ratio of net securitisation income of 3.62% in the first subperiod, whereas the magnitude of this change declines in the second subperiod to 1.47% only.

Furthermore, Columns 4, 5, and 6 of Table 2.11 show the results of evaluating the impact of monetary policy interest rates on the riskiness of securitisation activities. The coefficient on fed funds rate is positive and significant in the full sample and first sample subperiod, but negative in the second subperiod. Column 4 shows that a 100 basis point increase in fed funds rate leads to an increase in the adjusted Z-score of 1.19% in the full sample period, on average. Whereas, in the first subperiod (column 5), a 100 basis point increase in fed funds rate leads to an increase in the adjusted Z-score of 1.93%. Interestingly, the magnitude of this impact drops significantly in the second subperiod. Column 6 show that, on average, a 100 basis point increase in fed funds rate leads to a decrease in the the adjusted Z-score of only 0.86% in the second subperiod.

Overall, the results presented here support our previous evidence that the decline in monetary policy rates in the period that followed the global financial crisis has contributed to mitigating the destabilising impact of securitisation. On the one hand, our results show that changes in fed funds rates have positively affected both profitability and riskiness of securitisation activities in the run-up to and the period that followed the global financial crisis. On the other hand, the results show that the magnitude of this impact declines significantly in the period that followed the crisis, with a more dramatic decline in the case of riskiness of securitisation activities. Put together, these findings lead us to conclude that the decline in monetary policy interest rates have worked to mitigate the destabilising impact of securitisation in the aftermath of the global financial crisis.

2.7 Conclusion

This chapter considers the effects of securitisation on bank performance and stability. We examine how securitisation affects both bank profitability and risk and how these effects in turn determine the net impact of securitisation on bank stability and further on systemic risk at the banking system level. In particular, we develop a structural model of the bank performance and stability as a function of securitisation activities, that consists of a system of simultaneous equations. This approach enables us to simultaneously consider the effects of securitisation on bank profitability, risk and stability, while accounting for the two main channels through which securitisation affects profitability and risk, namely liquidity and cost of funding.

We find that there is a trade-off between profitability and risk of banks that engage in securitisation activities. The results also show that securitisation activities can explain this trade-off given that securitisation improves profitability but at the expense of increasing bank risk taking. Furthermore, we propose *S–score* as a measure of the net exposure of banks to securitisation activities. Analysis of the dynamics of this measure shows that securitisation activities have destabilising effect on securitiser banks. Further analysis explains the role of monetary policy in mitigating the destabilising effect of securitisation on banks in the period that followed the global financial crisis.

There have been several attempts to revive securitisation markets to boost banking efficiency and risk sharing in capital markets (Mersch, 2017). These attempts require a deep revision of the securitisation effects on both banks and financial markets to avoid any unintended consequences for bank performance and stability. This chapter provides a framework for regulators to think about the effects of securitisation at the bank level and the banking system level. It is important that regulators consider the effects of securitisation on a risk-adjusted performance basis, and to consider the different channels through which securitisation affects bank performance and stability.

Chapter 3

Margin Requirements and Systemic Liquidity Risk

Chapter 3: Margin Requirements and Systemic Liquidity Risk[1]

Abstract

We develop a model in which margin procyclicality and the propensity for liquidity hoarding interact to generate a systemic liquidity crisis. In this model, banks lend and borrow in the interbank market to mitigate liquidity risk and trade derivatives contracts in the OTC derivatives market to mitigate market risk. The daily mark-to-market of derivatives contracts results in daily margin calls that banks cover using high quality liquid assets. We find that distress due to margin procyclicality in the derivatives market can spillover to the interbank market leading to systemic liquidity risk. Interconnectedness further amplifies the effects of systemic risk within the interbank market. The model shows that central clearing might increase the possibility of systemic liquidity risk due to tight margin requirements and the timing of cash flows required from banks. We also find that haircut levels affect the possibility of systemic liquidity risk, and highlight the potential role of a market maker of last resort in limiting this possibility.

Keywords: Margin Procyclicality; Funding Liquidity Risk; Systemic Risk; Contagion; Networks; Agent-Based Modelling.

JEL Classification: G01; G15; G21; G28

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3.1 Introduction

The financial crisis of 2008 has highlighted the threats of interconnectedness to the stability of the financial system. In the aftermath of this crisis, central clearing of all standardised derivatives contracts has been enacted to reduce interconnectedness in over-the-counter (OTC) derivatives markets (Yellen, 2013).[2] In addition, the Bank for International Settlements (BIS) has issued similar margin requirements for non-centrally cleared derivatives (Bank for International Settleements and International Organization of Securities Commissions, 2013, 2015). As a result, the OTC market participants are now required to make margin payments at least daily in response to changes in the market value of their derivatives contracts.

In this chapter, we analyse the impact of margin requirements on funding liquidity risk of the OTC derivatives market participants. Previous work has focused on counterparty credit risk as in Acharya and Bisin (2014) who show that centralised clearing mechanisms provides transparency of trade positions which eliminates counterparty risk externality, and Loon and Zhong (2014) who suggest that introducing central clearing in the CDS market lowers counterparty credit risk and improves post-trade transparency and trading activity. In contrast, we consider the overlooked impact of margin requirements on funding liquidity risk of market participants. In particular, we consider margin procyclicality during times of high market volatility as a side effect of tight margin requirements. We focus on a specific question that has recently risen to the top of policy agendas: how does *margin procyclicality* in conjunction with *propensity for liquidity hoarding* affect the systemic risk propagation in the financial network of the interbank market?

[2]The Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 in the US and the European Market Infrastructure Regulation of 2012 in Europe both mandate central clearing of certain standardised and eligible OTC derivatives.

The impact of margin requirements on funding liquidity risk is a key concern for policy-making. On the one hand, variation margin which is required to be posted daily is significant compared to initial margin which is required only at the inception of a contract. According to the International Swaps and Derivatives Association (ISDA), at the end of first quarter of 2017, the initial margin and variation margin posted by derivatives dealers are estimated at $280.5 billion and $1131.2 billion, receptively (International Swaps and Derivatives Association, 2017). On the other hand, margin requirements focus on reducing counterparty credit risk through the mandate of daily mark-to-market and tight credit support annexes (CSA). Given that the amounts of variation margin calls can be large, there is significant liquidity risk from tight CSAs.

We develop a model that considers the impact of margin procyclicality on funding liquidity risk in the spirit of the seminal work of Brunnermeier and Pedersen (2009) who model the interaction between market liquidity and funding liquidity in centralised markets. They show that, under certain conditions, interbank haircuts are destabilising and market liquidity and funding liquidity are mutually reinforcing, leading to liquidity spirals. In the same vein, the ability of market participants in our model to meet margin requirements depends on their availability of funding. In our model, counterparty credit risk is mitigated by requiring banks to post daily cash margins to reduce exposure at default. If counterparties do not have sufficient cash to meet a margin call, they become distressed.

Our model considers bank behavior in both the OTC derivatives and the interbank markets. As in Faulkender (2005), we assume that banks trade in the OTC derivatives market for both hedging and speculation purposes. We also consider herding behavior in the interbank market as a driver of contagion similar to Acharya and Yorulmazer (2008). They show that banks engage in herding behavior in order to minimise the effect of bad information about other banks on their own borrowing costs while obtaining funding from depositors. In our model, banks engage in herding behavior while they raise liquidity and they have to decide between withdrawing their lending to other banks in the interbank market and using their less liquid assets as collateral to obtain funding.

Our model is populated with heterogeneous banks with varying features of size, balance sheet compositions, market risk exposures, and risk aversion. Banks trade derivatives contracts with each other in order to manage their exposures to market risk. A bank selects the direction of a derivatives contract based on its own risk aversion and idiosyncratic market risk exposure. For ease of exposition, we focus on the case of two types of banks with respect to risk aversion. The first is high risk-averse banks which aim to hedge their idiosyncratic market risk exposures and maintain net fixed interest rate exposure. The second is low risk-averse banks which speculate on market interest rate movements and accept to have net variable interest rate exposures.

We also show how the theory of multilayer networks can be used to analyse the spillover of distress from one segment of the financial market (OTC derivatives) to another one (interbank). In particular, we represent the OTC derivatives and interbank markets as two directed networks, where some banks participate in both networks while others participate in only one out of the two networks. We quantify the credit exposures that result from banks' derivatives positions in a network setting. These exposures change with changes in the market interest rates which leads to margin calls in order to reduce exposures at default. We then use this model to investigate some of the policy implications of margin requirements. To this end, the general approach followed is to perturb the OTC derivatives market with an interest rate shock and analyse the dynamics of contagion and systemic risk within the interbank market.

We find that margin procyclicality can lead to the onset of a systemic liquidity crisis within the interbank market. Furthermore, our model highlights the mechanism by which margin procyclicality can induce liquidity hoarding contagion in the interbank market. When a financially distressed bank refuses to rollover its current overnight lending to other institutions in the interbank market, it effectively transfers its distress to those institutions. As more institutions decide to hoard liquidity, a systemic liquidity crisis propagates within the interbank market. The model also shows that contagion can arise endogenously due to banks' propensity for hoarding liquidity during distress times. This contagion dynamic is thus characterised by a self fulfilling process among banks.

We also use the model to explore the impact of other factors on distress spillover and systemic liquidity risk. For instance, we show that central clearing might in fact increase the possibility of a systemic liquidity crisis due to tight margin requirements and the timing of cash flows required from banks. Also, consistent with previous evidence, the model predicts that interconnectedness amplifies the effect of systemic risk within the interbank market. Furthermore, the model shows that haircut levels affect the possibility of a systemic liquidity crisis, and highlights the potential role of a market maker of last resort in limiting this possibility. Finally, the results of our model illustrate the tension between the micro-level decisions of individual banks about their interbank lending and the macro-level outcomes of these decisions in the form of systemic loss that results from the cost of withdrawing interbank loans.

The rest of this chapter proceeds as follows. Section 3.2 provides an overview of related literature. Section 3.3 presents the market setup. Section 3.4 provides a model to analyse contagion and systemic risk due to margin procyclicality. Section 3.5 provides an overview of the model calibration and validation. Section

3.6 presents the results. Section 3.7 concludes the chapter.

3.2 Related Literature

Assessing the impact of the central clearing mandate and subsequent margin requirements on the OTC derivatives market has brought about much debate among academics, market participants and policy makers alike. Much of the discussions have involved the impact on collateral demand with a focus on the trade-off between the benefits of multilateral netting within a class of contracts against lost bilateral netting benefits across different classes. (Duffie and Zhu, 2011) are among the first studies to explore this trade-off. Their analytical framework highlights the role of the market network structure and netting arrangements in determining the change in collateral demand. Another strand of research has focused on counterparty credit risk. For instance, Acharya and Bisin (2014) shows that centralised clearing mechanisms provide transparency of trade positions which eliminates counterparty risk externality. Similarly, Loon and Zhong (2014) suggest that introducing central clearing in the CDS market lowers counterparty credit risk and improves post-trade transparency and trading activity. In contrast with previous work, we focus on the critical impact of margin requirements on funding liquidity risk. An impact that arises due to margin procyclicality which occurs when margin requirements rise at times of market stress, leading to even more stress.

This chapter contributes to the growing body of literature on financial contagion and systemic risk. We adopt a balance sheet approach similar to what is followed in the strand of literature on contagion that focuses on default cascades due to direct credit interlinkages among banks and solve for equilibrium as a fixed point mapping (see e.g. Eisenberg and Noe, 2001; Furfine, 2003; Freixas et al., 2000; Allen and Gale, 2000). We deviate, however, from this strand of literature in that we do not attempt to model cascade defaults due to payments shortage. Instead, we attempt to model distress cascades due to funding runs. Yet, another strand of literature use a similar balance sheet setting to model common asset holdings as a transmission mechanism for contagion (see e.g. Cifuentes et al., 2005; Krishnamurthy, 2010; Shleifer and Vishny, 2011; Caccioli et al., 2015*b*).

Liquidity hoarding is one of the main channels through which financial contagion spreads. We contribute to this literature by developing a model that illustrates liquidity hoarding due to margin procyclicality. Our work is closely related to the model of Gai et al. (2011) in which liquidity hoarding in the interbank market arises due to exogenous shocks to haircuts. We extend their framework to study the impact of margin procyclicality on funding liquidity risk and analyse its potential role in originating liquidity hoarding contagion in the interbank market. Similarly, Acharya and Skeie (2011) suggest that a bank's propensity to hoard liquidity in the interbank market is a function of its own rollover risk. The same notion is extended more in Acharya et al. (2011) whose model provides a micro-foundation for the funding risk of financial institutions with an extreme maturity mismatch between assets and liabilities. Anand et al. (2012) study bad news propagation within the interbank market and show how funding maturity and network structure interact to generate systemic financial crises. Brossard and Saroyan (2016) show that banks' liquidity influences the overnight rates in the interbank market and show that this is probably explained by hoarding and short-squeezing behaviors.

Another group of studies on liquidity hoarding uses information-theoretic models that combine liquidity shortages and Knightian uncertainty (Knight, 1921) to study flight to quality episodes (Caballero and Krishnamurthy, 2008). Similarly, Bolton et al. (2011) provide a model to determine the equilibrium mix of banks cash reserves and liquidity obtained through sales of assets. Allen et al.

(2009) show that it might be constrained efficient for banks to hoard liquidity if there is an increase in aggregate uncertainty about aggregate liquidity demand compared to idiosyncratic liquidity demand. Battiston et al. (2012*b*) highlight the role of connectivity in systemic risk propagation and show that a financial network is resilient to shocks to a specific limit, beyond which the network connectivity might exacerbate the systemic risk propagation. Diamond and Rajan (2011) show that banks might become illiquidity seekers to avoid realised losses due to asset fire sales and in anticipation of asset price recoveries. Eross et al. (2016) find evidence of endogenous responses and spillovers within the interbank market. Lopez-Espinosa et al. (2013) examine the impact of bank-specific factors on its solvency risk and show that funding risk is the main driver of systemic risk.

This chapter contributes also to the literature on procyclicality. One of the earliest models in this area is by Grossman and Miller (1988) which determines an equilibrium level of market liquidity based on the supply and demand for immediacy. In the same spirit, the seminal work of Brunnermeier and Pedersen (2009) links market liquidity and funding liquidity and shows that both margin spirals and losses spirals might result endogenously due to procyclicality. This chapter is also related to studies on margin procyclicality (see e.g. Murphy et al., 2014, 2016) and price procyclicality (see e.g. Danielsson et al., 2012; Danielsson and Zigrand, 2008). Another strand of models on procyclicality focuses on the link between leverage and market volatility. While some models focus on the endogenous determination of leverage when assets are used as collateral (see e.g. Geanakoplos, 2010; Fostel and Geanakoplos, 2012; Geanakoplos and Pedersen, 2012; Aymanns and Farmer, 2015), others focus instead on the impact of procyclical leverage on systemic risk (see e.g. Gorton, 2010; Gorton and Metrick, 2012; Tasca and Battiston, 2016).

This chapter contributes also to the strand of literature that suggests that banks behavior play a pivotal role in systemic risk propagation during distress times. For instance, Jones (2001) uses a network framework to model foreign exchange market trading decisions. Their model captures some behavioral aspects of currency trading and applies to arbitrage, hedging and speculation of currency risk. van den End and Tabbae (2012) investigate the behavioral responses by banks during the recent crisis. They show that these responses have been increasingly dependant across banks and provide an evidence of herding in the interbank market during the crisis. They also show that banks decisions regarding balance sheet adjustments have been procyclical. Other studies suggest that banks' decisions in the OTC derivatives market are motivated by both hedging and speculation. For instance, Géczy et al. (2007) use survey data and find that nonfinancial firms that have high earnings management incentives are more likely to use derivatives for speculative purposes. Additionally, Chernenko and Faulkender (2012) decomposes firms use of swap market to manage interest rate risk into hedging and speculation. Similar evidence is provided by Faulkender (2005) and Carter and Sinkey Jr (1998). Moreover, Gao et al. (2015) investigate the impact of the network structure on optimal hedge decisions and find that network features play an important role in determining corporate hedging decisions.

3.3 The Market Setup

In this section, we set up the market and develop a baseline model for the interactions between participants in this market.

3.3.1 Market Participants

The market consists of N banks and a single central counterparty denoted by H. Banks operate in both the OTC derivatives market where they trade derivatives contracts and in the interbank market where they can lend and borrow from each other. The liabilities of each bank are composed of interbank liabilities

L_i^B representing funding obtained from the interbank market (e.g. repo); other liabilities L_i^O; and capital K_i. On the assets side, a bank has interbank assets A_i^B representing funding extended to others in the interbank market (e.g. reverse repo); high quality liquid assets A_i^{HL}; low quality liquid assets A_i^{LL}; and other assets A_i^O. The balance sheet identity of a bank i can be expressed as:

$$A_i^B + A_i^{HL} + A_i^{LL} + A_i^O = L_i^B + L_i^O + K_i \tag{3.1}$$

Furthermore, the OTC market includes a single central counterparty denoted as H that provides central clearing services to banks. By clearing a derivatives contract, the central counterparty simultaneously becomes a counterparty to each one of the original parties of the contract and, thus, maintains a neutral position that can be expressed as:

$$\sum_{i=1}^{N} X_{Hi} = \sum_{i=1}^{N} X_{iH} \tag{3.2}$$

where X_{Hi} is the credit exposure of the central counterparty H to bank i, and X_{iH} is the credit exposure of bank i to central counterparty H.

3.3.2 Market Network

The market network is comprised of two layers: the OTC derivatives layer and the interbank layer. Both layers follow a core-periphery structure.

3.3.2.1 Network Construction

Craig and von Peter (2014) provide a formal way of constructing a core-periphery network using a block model by which they represent the interbank market. In their model the core banks interact (i.e. lend and borrow) with each other and with other periphery banks. The model sets some restrictions on constructing the network: i) it requires that a core bank be connected to all other core banks; ii) it allows interactions between core and periphery banks; and iii) it does not allow connections between any pair of periphery banks. However, not all financial networks show this exact core-periphery structure. Anand et al. (2018) show that some actual core-periphery financial networks can deviate greatly from a perfect structure as that one suggested by Craig and von Peter (2014).

We use a modified version of the block model of Craig and von Peter (2014) to construct both layers of the market network. We relax the first restriction to allow for high probability of connection among core banks but not necessarily to produce a complete network among them. Our modified block model can be represented as:

$$\underbrace{\begin{bmatrix} CC & CP \\ PC & PP \end{bmatrix}}_{Blocks} \Leftrightarrow \underbrace{\begin{bmatrix} \rho^{CC}\ (High) & \rho^{CP}\ (Low) \\ \rho^{PC}\ (Low) & \rho^{PP}\ (Zero) \end{bmatrix}}_{Probablity\ of\ Connection}$$

where block CC represents the interaction among core banks with a connection probability of ρ^{CC} which is expected to be high, blocks CP and PC represent the interactions among core banks and periphery banks with connection probabilities of ρ^{CP} and ρ^{PC} which are equal and are expected to be low, while block PP represents the interaction among periphery banks which we restrict its probability ρ^{PP} to zero. Core banks are determined based on their relative size in the network.

Thus, we construct a market network comprising of two layers. The first layer represents the interbank market. The probability of a connection between two core banks in this layer is equal to ρ^{CC}. Also, the probability of a connection between a core bank and a periphery bank is set to ρ^{CP}. The number of core banks is determined from an empirical data on interbank network as shown in Section 3.5. A wiring algorithm is then used to initialize the connections between banks which generates the adjacency matrix $[\Theta_{ij}]_{\{i,j=1,2,\ldots,N\}}$. Links in the interbank layer represent interbank loans, where A^B_{ij} is a loan extended from bank i to bank j. The value assigned to each link depends on the relative value of the interbank assets of the two banks connected by this link. The value of an interbank loan given by i to j, $A^B_{ij} = L^B_j \frac{A^B_i}{\sum_i \Theta_{ij} A^B_i}$. Total interbank liabilities can be estimated as $L^B = \sum_{i=1}^N L^B_i$, and total interbank assets can be estimated as $A^B = \sum_{i=1}^N A^B_i$. Finally, total interbank assets equal total interbank liabilities given that a bank's interbank liability is another bank's asset.

The second layer represents the OTC derivatives market and depicts the long term relationships in the OTC derivatives market. This layer consists of N banks and a single central counterparty. Each link in this layer represents a potential counterparty from which a bank can choose to enter a derivatives contract with. The number of core banks is determined from empirical data on an OTC derivatives network as shown in Section 3.5. A wiring algorithm is used to initialize connections between banks. All core banks are connected to the central counterparty, while they are connected to each other with a probability ρ^{CC}. Periphery banks are connected to core banks with a probability ρ^{PC}, but they do not connect to each other or the central counterparty. It is worth noting, though, that core banks and the connections of each bank are not necessarily the same in both the OTC derivatives and the interbank layers.

3.3.2.2 Network Connectivity

We use two measures of centrality that are widely used in network analysis to measure interconnectedness of a network: density and degree centrality (Newman, 2010*b*). Density provides a measure of the overall connectivity of the network. It is estimated as the ratio of actual links to the total number of possible links in the network. A rough estimation of this measure can be obtained from the adjacency matrix of each layer of the network. Let d be the density of the interbank layer, it can then be estimated as:

$$d = \frac{\rho^{CC} \cdot N^{CoreB} \cdot (N^{CoreB} - 1)/2 \ + \ \rho^{CP} \cdot N^{CoreB} \cdot (N - N^{CoreB})}{N^{CoreB} \cdot (N^{CoreB} - 1)/2 \ + \ N^{CoreB} \cdot (N - N^{CoreB})} \tag{3.3}$$

where N^{CoreB} is the number of core banks in the interbank layer. Furthermore, degree centrality provides a measure of the connectivity of an individual bank. In a given network, degree k_i of a bank i is the total number of links it has with other banks. We also distinguish between two measures of degree centrality in the interbank layer. The in-degree k_i^{in} (out-degree k_i^{out}) which represents the number of links in which the bank is the lender (borrower), where:

$$k_i = k_i^{in} + k_i^{out} \tag{3.4}$$

Both measures can be estimated for the OTC derivatives layer similar to the interbank layer.

3.3.3 OTC Derivatives Market Dynamics

In this section, we describe a baseline model of interactions between banks in the OTC derivatives market.

3.3.3.1 Trading Strategies

Banks can use the OTC derivatives market for hedging or speculation as shown by Faulkender (2005). We further assume that a bank's decision to hedge or speculate is determined by two factors, namely its idiosyncratic market risk exposure and its level of risk-aversion.

A bank with a given risk exposure may decide to hedge this exposure by taking a position in the opposite direction, or to speculate on market movements by taking a position in the same direction. Other banks with no risk exposures to manage still can speculate on market movements. We further assume that all banks are risk-averse, meaning that they accept to take more risk only if justified by higher expected returns. However, they have different levels of risk-aversion. That said, we divide banks into two types low risk-averse and high risk-averse.

The decisions of high risk-averse bank are limited to hedging, while low risk-averse bank can take hedging or speculation decision.

Based on the combinations of idiosyncratic exposure and risk-aversion level, three trading strategies are available for banks in the OTC derivatives market as follows:

A- **Hedging** which can be followed in cases of a low risk-averse bank with an existing idiosyncratic exposure, or a high risk-averse bank with an existing idiosyncratic exposure.

B- **Speculation** which might be followed in cases of a low risk-averse bank with an existing idiosyncratic exposure, or a low risk-averse bank without an existing idiosyncratic exposure.

C- **No-Action** which might be followed in case of a high risk-averse bank without an existing idiosyncratic exposure.

The purpose for which a bank uses the OTC derivatives market determines its vulnerability to market risk. Banks face market risk to the extent that their positions are not hedged.

3.3.3.2 Trading Mechanism

Banks use the OTC derivatives market to manage their idiosyncratic risk exposures based on the trading strategies outlined above. For simplicity, we assume that banks are only exposed to idiosyncratic interest rate risk exposures. Additionally, we assume that the only way that banks can hedge or speculate interest rate movements is via the OTC derivatives market using a plain vanilla fixed-for-floating interest rate swap based on a given benchmark market interest rate. Also, trading in the OTC derivatives market is governed by a specific set of rules as follows:

1- Periphery banks trade with core banks.

2- Periphery banks do not trade with other periphery banks.

3- Core banks trade with other core banks.

4- Core banks have no constraints on their capacity to enter into contracts with periphery banks.

5- Each bank trades based on its own strategy (see 3.3.3.1).

3.3.3.3 Clearing Mechanism

Derivatives contracts can either be bilaterally or centrally cleared. In either case, cleared contracts generate credit exposures which we quantify below.

For banks i and j, let X_{ij}^c be the amount that j owes i in position of contract c. It then follows that $max(X_{ij}^c; 0)$ is the exposure of i to j in contract c. This exposure is the amount counterparty i risks losing upon the default of counterparty j. Also, let C^{ij} be the set of all outstanding contracts between i and j. It follows that the net exposure of i to j can be expressed as $X_{ij} = max\left\{\sum_{c=1}^{C^{ij}} X_{ij}^c \quad , \quad 0\right\}$. Furthermore, let X_i be the aggregate exposure of i. If all i's contracts are bilaterally cleared, it is exposed to different counterparties, and its net exposure can be expressed as:

$$X_i = \sum_{j \neq i}^{N} max\left\{\sum_{c=1}^{C^{ij}} X_{ij}^c \quad , \quad 0\right\} \tag{3.5}$$

Similarly, if all i's contracts are centrally cleared, i is exposed only to the central counterparty H. Let C^{iH} be the set of all i's outstanding contracts that are centrally cleared with H, and X_{iH}^c be the exposure of i to H in contract c. It follows that i's net exposure can be expressed as:

$$X_i = max\left\{\sum_{c=1}^{C^{iH}} X_{iH}^c \quad , \quad 0\right\}. \tag{3.6}$$

Finally, let us assume that a percentage ω of all i's contracts is centrally cleared, while $(1 - \omega)$ is bilaterally cleared, and that C^i is the set of all i's outstanding contracts where $C^i = C^{iH} + \sum_{j\neq i}^{N} C^{ij}$, $C^{iH} = \omega \times C^i$ and $\sum_{j\neq i}^{N} C^{ij} = (1-\omega)\times C^i$. Thus, the net exposure of i to the central counterparty H and all other counterparties $j \neq i$ can be obtained by combining Equations 3.5 and 3.6 as follows:

$$X_i = \underbrace{max\left\{\sum_{c=1}^{C^{iH}} X_{iH}^c \quad , \quad 0 \right\}}_{Centrally\ Cleared} + \underbrace{\sum_{j\neq i}^{N} max\left\{\sum_{c=1}^{C^{ij}} X_{ij}^c \quad , \quad 0\right\}}_{Bilaterally\ Cleared} \tag{3.7}$$

3.3.3.4 Margin Calls

A cleared contract results in two types of exposures: the potential future exposure which is mitigated by the initial margin, and the current exposure which is mitigated by variation margin (Lin and Surti, 2015). Given our focus on margin procyclicality due to market fluctuations, we use a single measure to quantify both exposures as illustrated in 3.3.3.3. Hence, we do not explicitly consider a contract's initial margin. Instead, our focus here is on variation margin.

The market value of the swap contract changes with market fluctuations. More specifically, the sensitivity of the swap value to changes in the market interest rate can be approximated by modified duration (Smith, 2011). Following the same logic, we approximate the modified duration of a swap contract by β which represents the sensitivity of the swap value to a one basis-point change in the benchmark market interest rate R_m. Thus, for the pay-fixed side (long) of a swap contract, the basis-point change in the swap's market value ΔV can be estimated as a function of the change in market interest rate ΔR_m and β as follows:

$$\Delta V = \beta \cdot \Delta R_m \tag{3.8}$$

where ΔV is measured per dollar of notional amount, and ΔR_m is measured in basis points. We estimate the change in market interest rate as a stochastic process using the Hull-White single factor model (Hull and White, 1990). For the receive-fixed side (short), the change in the swap's market value is $-\Delta V$. For instance, if market interest rates increase, the new swap rates will be higher. As a result, the pay-fixed side of the swap makes a profit as the market value of its contract increases, while the receive-fixed side makes a loss due to the decline in the market value of its contracts. This implies that the direction of ΔV depends on the direction of ΔR_m.

Due to changes in the market value of the swap contracts outstanding between banks i and j, the net exposure of i to j fluctuates leading to variation margin calls if necessary. If i's aggregate exposure to j increases, i should recehive a variation margin from j, and vice versa. Let ΔX_{ij} be the the aggregate change of i's exposure to j, it follows from Equation 3.8 that:

$$\Delta X_{ij} = \underbrace{\sum_{c=1}^{C^{ij+}} \Delta V \cdot B^c}_{Pay-fixed} + \underbrace{\sum_{c=1}^{C^{ij-}} - \Delta V \cdot B^c}_{Receive-fixed} \tag{3.9}$$

where B^c is the notional amount of contract c. C^{ij+} and C^{ij-} are the set of all contracts between i and j in which i is the pay-fixed side and pay-floating side, respectively. Now, let v_{ij} be the variation margin required from bank i and due to bank j, it then follows that:

$$v_{ij} = max\left\{\Delta X_{ji} \quad , \quad 0\right\} \tag{3.10}$$

where ΔX_{ji} is the the aggregate change of j's exposure to i which is equal to $-\Delta X_{ij}$. Following the same intuition as in Equations 3.5-3.7, the total variation margin required from bank i, v_i, can be estimated as:

$$v_i = \underbrace{v_{iH}}_{Centrally\ Cleared} + \underbrace{\sum_{j \neq i}^{N} v_{ij}}_{Bilaterally\ Cleared} \tag{3.11}$$

where v_{iH} is the variation margin required from i and due to the central counterparty H. We discuss how banks meet their variation margin calls in the following section.

3.4 Contagion and Systemic Risk

In this section, we analyse the potential contagion in the interbank market due to distress spillover from the OTC derivatives market.

3.4.1 Distress Origination

As illustrated in 3.3.1, banks have holdings of both high quality liquid assets A^{HL} and low quality liquid assets A^{LL}. Variation margin calls can only be paid using A^{HL}, but not A^{LL}. This implies that banks may come under distress if their holdings of A^{HL} are not sufficient to cover a margin call. To illustrate this, assume that due to high market interest rates volatility, a bank i is faced with an outsize variation margin call. Formally, the condition under which bank i becomes *distressed* is:

$$A_i^{HL} - v_i \quad < \quad 0 \tag{3.12}$$

Equation 3.12 implies that sufficiently high variation margins have the potential to trigger a liquidity shortage at the bank. If a bank faces such a liquidity shortage, it needs to take defensive actions to avoid defaulting on required payments. We assume that the only way banks can obtain new funding is through the interbank market.

3.4.2 Price of Liquidity

Distressed banks with insufficient holdings of A^{HL} have two options to secure funding to cover their variation margin calls. The first is to withdraw their lending extended to other banks in the interbank market. In this case, the bank pays exit fees for prematurely calling the loan. Let γ_i be the exit fees that the bank i has to pay. Thus, the maximum amount of A^{HL} that i can obtain by withdrawing its lending from the interbank market is given by:

$$A_i^{HL} = (1 - \gamma_i)A_i^B \tag{3.13}$$

The second option available for distressed banks to secure additional funding is to use A^{LL} as collateral to obtain A^{HL} from the interbank market. In this case, the bank is faced with two types of haircut that will be applied to A^{LL}. The first is a system-wide haircut $\alpha \in [0,1]$ which reflects the perceived system wide liquidity risk of A^{LL} compared to A^{HL}. The second is a bank-specific haircut $\alpha_i \in [0,1]$ to reflect the idiosyncratic risk associated with a given bank. Therefore, the maximum amount of A^{HL} that bank i can obtain using its holdings of A^{LL} as collateral is given by:

$$A_i^{HL} = (1 - \alpha - \alpha_i)\ A_i^{LL} \tag{3.14}$$

where $\alpha + \alpha_i < 1$, which is necessary to put a non-negative lower bound on the amount of A^{HL} obtained using A^{LL}.

A bank's decision to follow a specific funding option of the above depends on its cost to the bank. Thus, it follows from Equations 3.13 and 3.14 that liquidity hoarding will continue as long as it is less costly compared to using less liquid assets as collateral. Formally, when:

$$\gamma_i < (\alpha + \alpha_i) \tag{3.15}$$

In other words, when the amount of A^{HL} that a bank can obtain by withdrawing a given amount of interbank lending is higher than the amount of A^{HL} that can be obtained by pledging an equal amount of less liquid assets.

3.4.3 Liquidity Hoarding Contagion

When banks decide to withdraw their lending from the interbank market, this may lead to a liquidity hoarding contagion. We propose a liquidity hoarding contagion mechanism in the spirit of (Gai et al., 2011). To illustrate the dynamics of this liquidity hoarding contagion, assume that a bank i becomes distressed as illustrated by Equation 3.12. According to Equation 3.15, the bank hoards liquidity from the interbank market to cover its liquidity shortage if $\gamma_i < (\alpha + \alpha_i)$. Further, assume that the bank withdraws an additional amount of interbank lending as a precautionary action for subsequent margin calls. This amount can be estimated as a fraction of its current margin call v_i. Let A_i^h be the amount hoarded which can be estimated as:

$$A_i^h = \frac{(1+\lambda)v_i - A_i^{HL}}{(1-\gamma_i)} \tag{3.16}$$

where λ is called the liquidity hoarding multiplier. Similarly, if $\gamma_i > (\alpha + \alpha_i)$, the bank sells an amount of its less liquid assets to cover its liquidity shortage and obtain the precautionary liquidity. Let A_i^s be the amount sold which can be estimated as:

$$A_i^s = \frac{(1+\lambda)v_i - A_i^{HL}}{(1-\alpha-\alpha_i)} \tag{3.17}$$

Now assume that i is connected to a group of k_i^{in} banks through its interbank lending transactions. Also, assume that bank i's interbank withdrawals are proportionally distributed among its borrowers. For contagion to spread beyond i, there should be at least one bank $j \in k_i^{in}$ for which the following condition holds:

$$A_j^{HL} - v_j - \left(A_{ij}^B \cdot \frac{A_i^h}{A_i^B}\right) < 0 \tag{3.18}$$

Equation 3.18 provides the tipping point for liquidity distress, that arises at bank i, to become systemic and spread to other banks.

Once bank i starts to hoard liquidity and Equation 3.18 is satisfied for other banks, liquidity shortages can propagate through the network of interbank linkages. Subsequently, we can derive the general condition under which any bank j becomes distressed as follows:

$$A_j^{HL} - v_j - \left(\sum_{i}^{k_j^{out}} A_{ij}^B \cdot \frac{A_i^h}{A_i^B} \right) < 0 \tag{3.19}$$

where k_j^{out} is the group of bank j lenders. Thus, a bank becomes distressed if the total amount of its available A_j^{HL} is not sufficient to cover its variation margin, after accounting for the loss of interbank funding that it might experience due to liquidity hoarding by its counterparties.

3.4.4 Systemic Risk

Finally, we estimate the overall impact of distress spillover from the OTC derivatives market as the cost of liquidity hoarding in the interbank market and the cost of selling less liquid assets. We then estimate the systemic loss as the ratio of this amount to the initial amount of interbank assets. It then follows that:

$$\Phi = \frac{\sum_{i=1}^{N} \gamma_i A_i^h \quad + \quad \sum_{i=1}^{N} (\alpha + \alpha_i) A_i^s}{\sum_{i=1}^{N} A_i^B} \tag{3.20}$$

where Φ is an approximation to the systemic loss that the system encounters due to liquidity hoarding or selling less liquid assets.

3.5 Model Calibration and Validation

In this section, we calibrate the parameters used in the model to approximate the basic characteristics of the OTC derivatives and interbank markets, and provide an overview of the simulation framework.

3.5.1 Model Calibration

TABLE 3.1: Description of parameters and their initial values that are used in the baseline simulation. The values of some parameters are determined endogenously during each run.

Parameters	Description	Baseline Values
N	Number of banks	245
N^{CoreB}	Number of core banks in the interbank layer	16
N^{CoreD}	Number of core banks in the OTC derivatives layer	9
A_i^B	Interbank assets of bank i	$\approx U(0.1\%, 10\%)$ of total assets
A_i^{HL}	High-quality liquid assets of bank i	$\approx U(1\%, 5\%)$ of total assets
A_i^{LL}	Low-quality liquid assets of bank i	$\approx U(10\%, 30\%)$ of total assets
A_i^O	Other assets of bank i	Residual
L_i^B	Interbank liabilities of bank i	Endogenous
L_i^O	Other liabilities of bank i	Residual
K_i	Capital of bank i	$\approx U(7\%, 15\%)$ of total assets
ρ^{CC}	Probability of core-to-core connection	0.65
ρ^{CP}	Probability of core-to-periphery connection	0.15
ρ^{PP}	Probability of periphery-to-periphery connection	0.00
ΔR_m	Change in market interest rate in basis points	60
ω	Central clearing percentage	72%
β	Measure of modified duration	2
λ	Liquidity hoarding multiplier	1
γ	Liquidity hoarding cost	$\approx U(0\%, 5\%)$
α	System-wide haircut	10%
α_i	Bank-specific haircut	$\approx U(0\%, 5\%)$

We calibrate the model using data of the US banking system as of 31 December 2016.[3] Table 3.1 displays the values used. Given that we are interested in banks that are active in both the OTC derivatives market and the interbank market, we base our parameters estimation on the group of insured commercial banks with assets greater than \$3 billion. That said, we set the number of banks in our model equal to 245. For each bank, the amount of total assets is set as $A_i \in [100; 70,000]$ which are drawn from a powerlaw distribution with power law exponent of 1.75 which is estimated directly from the data set. The composition of each bank's balance sheet is determined randomly as percentages of total assets with parameters drawn from uniform distributions as follows. The ratio of interbank assets $A_i^B \approx U(0.1\%, 10\%)$, the ratio of high quality liquid assets $A_i^{HL} \approx U(1\%, 5\%)$, the ratio of low quality liquid assets $A_i^{LL} \approx U(10\%, 30\%)$, the ratio of interbank liabilities $L_i^B \approx U(0.1\%, 10\%)$, and the ratio of equity $K_i \approx U(7\%, 15\%)$. Finally,

[3] Data is obtained from the web site of the Federal Financial Institutions Examination Council (FFIEC) and is available at https://www.ffiec.gov/nicpubweb/nicweb/nichome.aspx

other assets are set as $A_i^O = A_i - (A_i^B + A_i^{HL} + A_i^{LL})$, and other liabilities are set as $L_i^O = A_i - (L_i^B + K_i)$.

We construct the market network of both the interbank and the OTC derivatives layers as a core-periphery structure following (Craig and von Peter, 2014). The number of core banks is determined based on the relative size of each bank's assets in a specific layer of the network. To estimate this, we first rank banks and calculate the difference in the log of assets of each bank and its succeeding bank. Banks with difference higher that 0.10 are taken to be the core banks. Based on this, the number of core banks in the interbank layer is set equal to 16 banks, and in OTC derivatives layer is set equal to 9 banks. The core-core probability of connection ρ_{CC} is set equal to 0.65, and the core-periphery probability of connection ρ_{DC} is set equal to 0.15.

The percentage of centrally cleared contracts is set equal to 72% as reported by the International Swaps and Derivatives Association in its OTC Derivatives Market Analysis on interest rate derivatives published in December 2016 (International Swaps and Derivatives Association, 2016). Following the interest rate swaps stress test developed by the Commodities and Futures Trading Commission (Commodity Futures Trading Commission, 2016), we use a market interest rate change of 60 basis points to estimate the change in value of the swap contracts. In addition, we use a system wide haircut percentage of 10% similar to that percentage recommended by the Bank for International Settlements (Bank for International Settleements and International Organization of Securities Commissions, 2013). The bank specific hair cut α_i is drawn from a uniform distribution $U(0\%, 5\%)$. We set the sensitivity of a derivatives contract value to market interest rate risk β equal to 2, and the liquidity hoarding cost $\approx U(0\%, 5\%)$. Finally, we set the liquidity hoarding multiplier equal to 1 as in Gai et al. (2011).

3.5.2 Model Validation

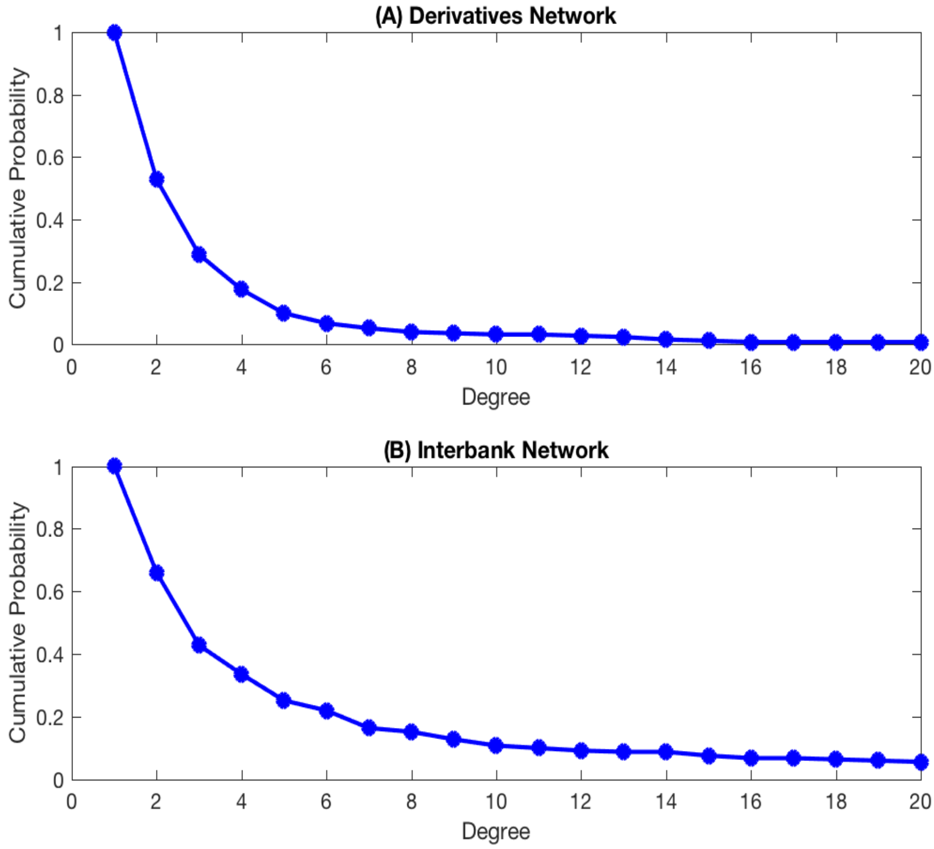


FIGURE 3.1: Degree distribution of both the derivatives and the interbank layers of the market network. The figure shows the cumulative density function (CDF) of the degree distribution based on the average of 100 simulations.

We validate the model to confirm that it produces interbank and OTC derivatives markets that resemble the real markets based on individual bank decisions on trading in the OTC derivatives market. The model is validated based on a comparison between the features of the model's network topology and those features observed in read data.

Degree distribution of both the derivatives and the interbank layers of the market network are shown in Figure 3.1. The figure shows the cumulative density function (CDF) of the degree distribution. The power law exponents are 1.75 in the case of the interbank layer and 2.15 in the case of the derivatives layer. Overall, these distributions show a good match with typical core-periphery networks from different markets including Germany (Craig and von Peter, 2014), Italy (Fricke and Lux, 2015), Mexico (Martinez-Jaramillo et al., 2014), U.K. (Langfield et al., 2014), and U.S. (Li and Schürhoff, 2014; Markose et al., 2012).

3.6 Results

In this section, we describe the main results of this chapter. We first provide an overview of the simulations framework. Then, we provide the results of a baseline simulation based on the initial parameters as shown in Table 3.1. Finally, we extend the analysis to explore the impact of central clearing, interconnectedness and other factors on the distress spillover from the OTC derivatives market to the interbank market.

3.6.1 Simulations Framework

The procedure of the model is illustrated by Figure 3.2 and by the flowchart in Figure 3.3. At the beginning of the simulation, $t = 0$, banks' balance sheets, the interbank network are set up according to the initial values of parameters as shown in Table 3.1. At $t = 1$, banks develop their own strategies, then trading and clearing take place in the OTC derivatives market as shown in Section 3.3.3. At $t = 2$, margin calls are calculated as derived in Equation 3.11. For each bank, distress is assessed based on Equation 3.12. Then, based on the available funding options, the tipping point for liquidity hoarding contagion is assessed as in Equation 3.18. Finally, systemic loss is approximated as shown by Equation 3.20.

We typically run 100 simulations and report the average. The main output of each simulation is the systemic loss due to liquidity hoarding and the number of distressed banks. The baseline simulation is based on the initial values of

t = 0	t = 1	t = 2
Set up banks' balance sheets Set up interbank network	Trading Strategies Trading and Clearing	Margin Calls Spillover Contagion Systemic Risk

FIGURE 3.2: Simulation Framework

the model parameters. Some of these values are adjusted in the subsequent experiments to test other hypotheses.

3.6.2 Systemic Liquidity Risk

As a benchmark, we begin by analysing the dynamics of distress spillover from the OTC derivative market to the interbank market. The main factor of impact here is margin procyclicality as derived by the change in the benchmark market interest rate ΔR_m. The change in ΔR_m affects all contracts simultaneously. This is similar to a parallel shift in the zero yield curve. We do not explicitly model any convexity effect of the interest rate change as the modified duration β is assumed to account for this effect. Figure 3.4 shows the systemic loss and the number of distressed banks over a range of 0 to 100 basis point of ΔR_m.

The dynamics of systemic risk captured in this figure varies as follows. At low levels of ΔR_m, the change in value of derivatives contracts is limited and lead only to normal variation margin calls that can be met by normal holdings of high quality liquid assets. The level of systemic risk in this case is at its minimum level and none of the banks is distressed. As the level of ΔR_m increases to moderate levels, the distress spillover tipping point is reached. The change in value of derivatives contracts lead to variation margin calls that exceed the holdings of high quality liquid assets of some banks. The only option available for these banks to fund their margin calls is to hoard liquidity from the interbank market. This is due to the fact that in our benchmark model the liquidity hoarding cost is less than the total haircut that these banks might be subject to if they try to

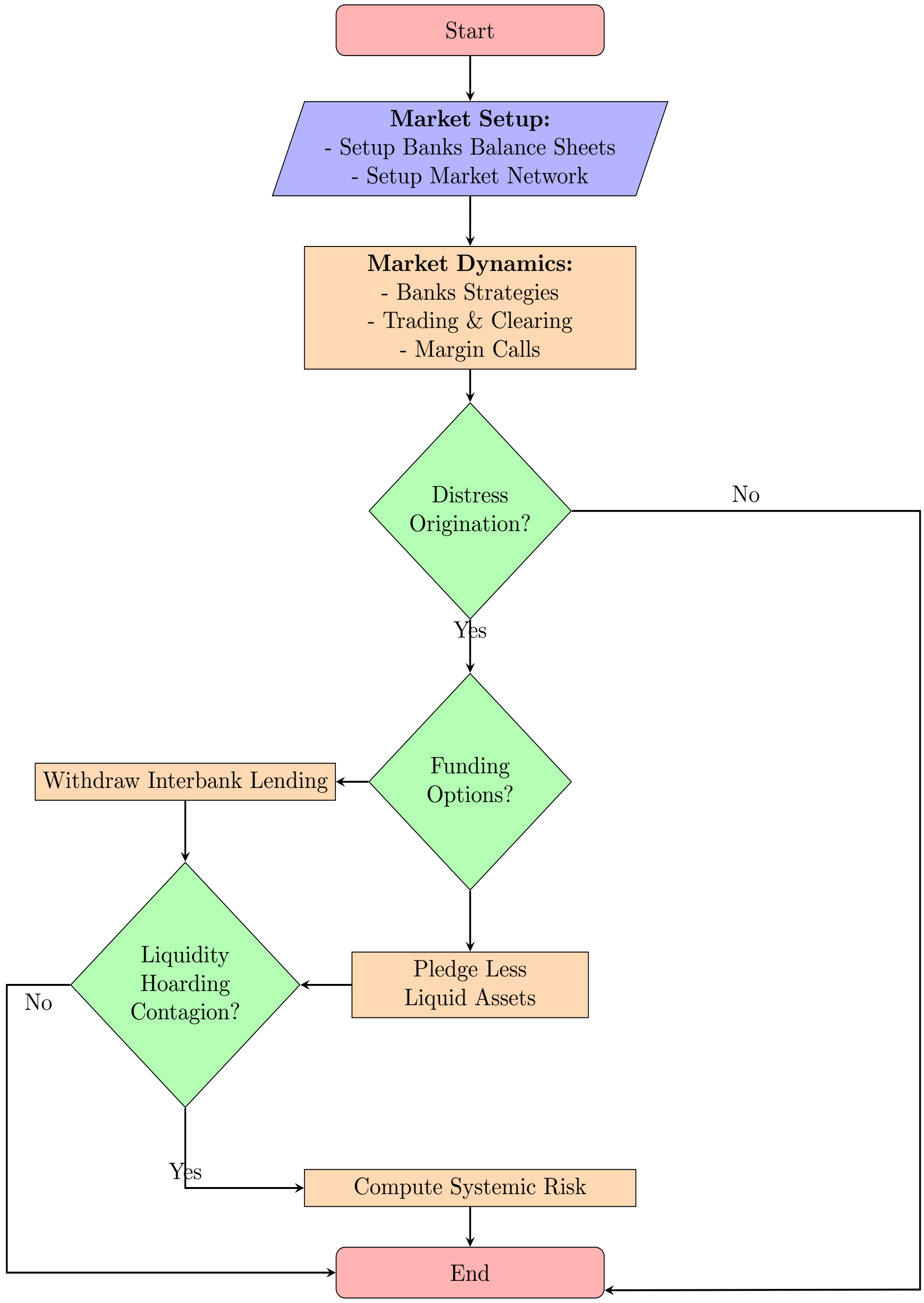


FIGURE 3.3: A flowchart that represents the steps of the model.

sell less liquid assets. The level of systemic risk at this stage is still limited due to the fact that distressed banks are small banks with limited share in the interbank lending and borrowing activities. At high levels of ΔR_m, the change in value of

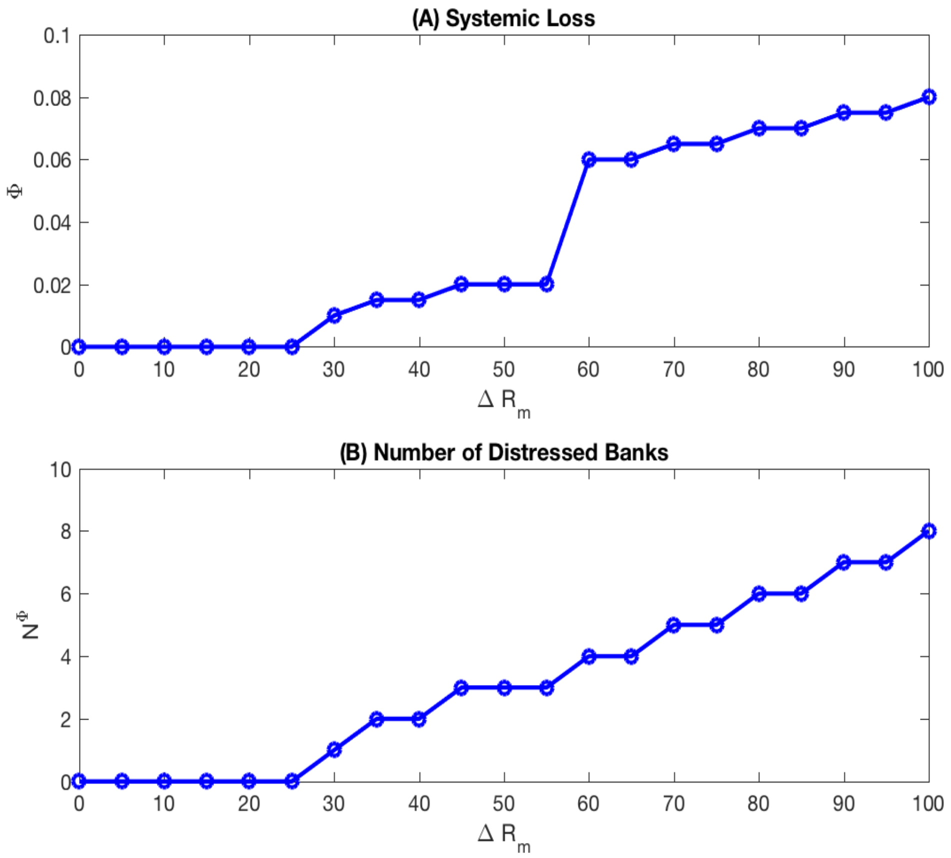


FIGURE 3.4: Stylised Systemic Liquidity Crisis. The simulation runs using parameters in Table 3.1. Φ is the systemic loss due to liquidity hoarding, N^{Φ} is the number of distressed banks and ΔR_m is the basis point change in the benchmark market interest rate. The result is based on the average of 100 simulations.

derivatives contracts becomes significant and the number of banks with variation margin calls that exceed their normal holdings of high quality liquid assets increases. At this stage, the level of systemic risk becomes significant due to the fact that some interbank dealers become distressed. When a dealer decides to hoard liquidity, systemic loss increases significantly because of the dealer's large share in the interbank lending and borrowing activities.

Thus, our benchmark model seems to be consistent with the findings of Lee (2013) that the interbank market can be vulnerable to systemic liquidity shortages due to knock-on effects through interbank linkages. Our findings are also consistent with the evidence on herding in the interbank market during the financial crisis of 2008 (van den End and Tabbae, 2012). Moreover, these findings give rise to the importance of prudent liquidity risk management practices at the bank level that consider systemic implications of financial distress. Banks should maintain sufficient liquidity to limit the chances that high margin requirements would cause liquidity distress for them. In addition, the impact of market volatility should be adequately accounted for when setting liquidity coverage ratios of banks as required by the new Basel III standards.

3.6.3 Impact of Central Clearing

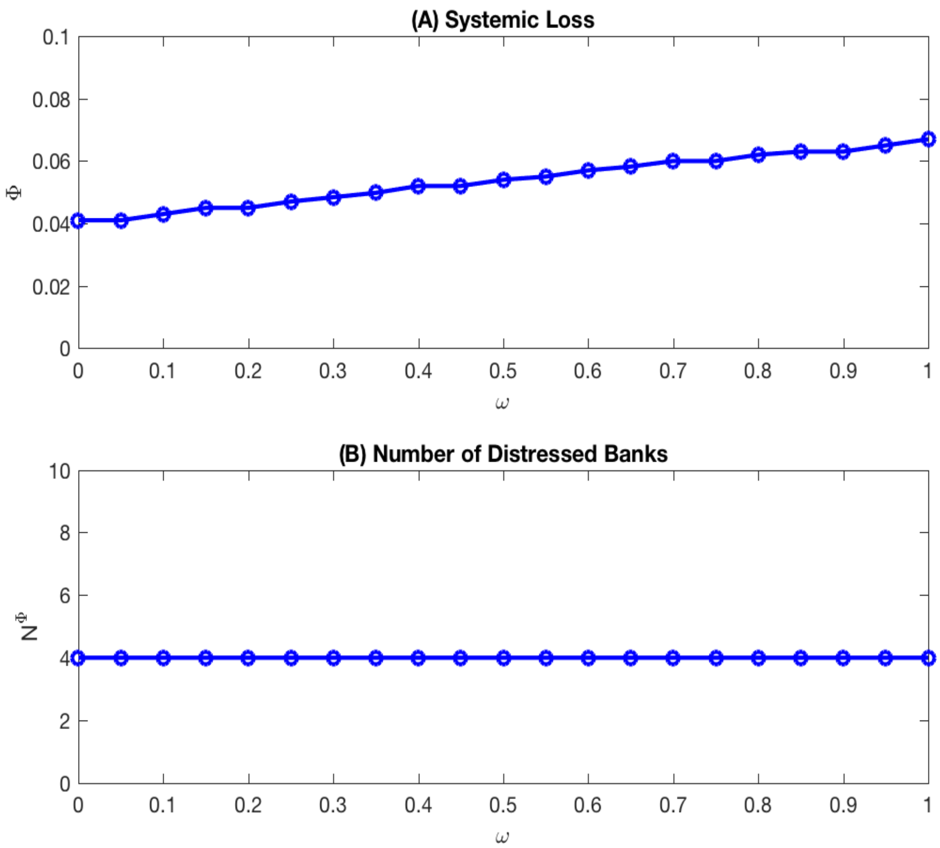


FIGURE 3.5: Impact of central clearing on systemic liquidity risk. The simulation runs using parameters in Table 3.1 with varying central clearing percentage values. Φ is the systemic loss due to liquidity hoarding, N^{Φ} is the number of distressed banks and ω is the percentage of central clearing. The result is based on the average of 100 simulations.

We now move to assess the impact of central clearing compared to bilateral clearing on the distress spillover from the OTC derivatives market into the interbank market. We assume that an average percentage ω of all the derivatives contracts traded is centrally cleared through the central counterparty. However, unlike the benchmark case in which we calibrate ω to be 72%, here we assess systemic risk over the whole range of central clearing from 0% to 100%.

Figure 3.5 shows the results of this exercise which reveal a striking finding. The percentage of centrally cleared contracts compared to bilaterally cleared contracts positively affects the systemic risk propagation within the interbank market. The systemic liquidity hoarding increases with ω, although not significantly. One reason that explains this finding is the difference in the timing of cash flows under central and bilateral clearing. Although the value of margin calls are the same, in practice the timing of cash flows is different. In the case of central clearing, banks with negative values are required to post their margin requirements immediately while banks with positive values receive their margin in the following period. Conversely, in the case of bilateral clearing all cash flows are received at the same period. This implies that banks can use these receipts from margin calls as caution against sudden liquidity withdrawal which limits the systemic liquidity risk in the case of bilateral clearing compared to central clearing.

Our findings about the impact of central clearing on systemic liquidity risk complements previous studies that focus on its impact on counterparty credit risk (e.g. Acharya and Bisin, 2014; Loon and Zhong, 2014) and collateral demand (e.g. Duffie and Zhu, 2011; Cont and Kokholm, 2014; Garratt and Zimmerman, 2015). We focus on the day-to-day margining and funding practices in OTC derivatives markets. Our finding that central clearing might in fact increase systemic liquidity risk sheds light on the overlooked impact of margin requirements on funding liquidity risk. An impact that arises due to margin procyclicality which occurs when margin requirements rise at times of market stress, leading to even more stress. Also, these findings emphasise the need of banks to consider the impact of central clearing on their margin requirements and accordingly liquidity risk management. Banks with derivatives exposures that are being moved from bilateral clearing to central clearing as required by regulations should expect increases in required daily cash flows to meet their margin requirements. Thus, banks should adequately account for this adverse impact of central clearing when setting liquidity coverage ratios.

3.6.4 Impact of Interconnectedness

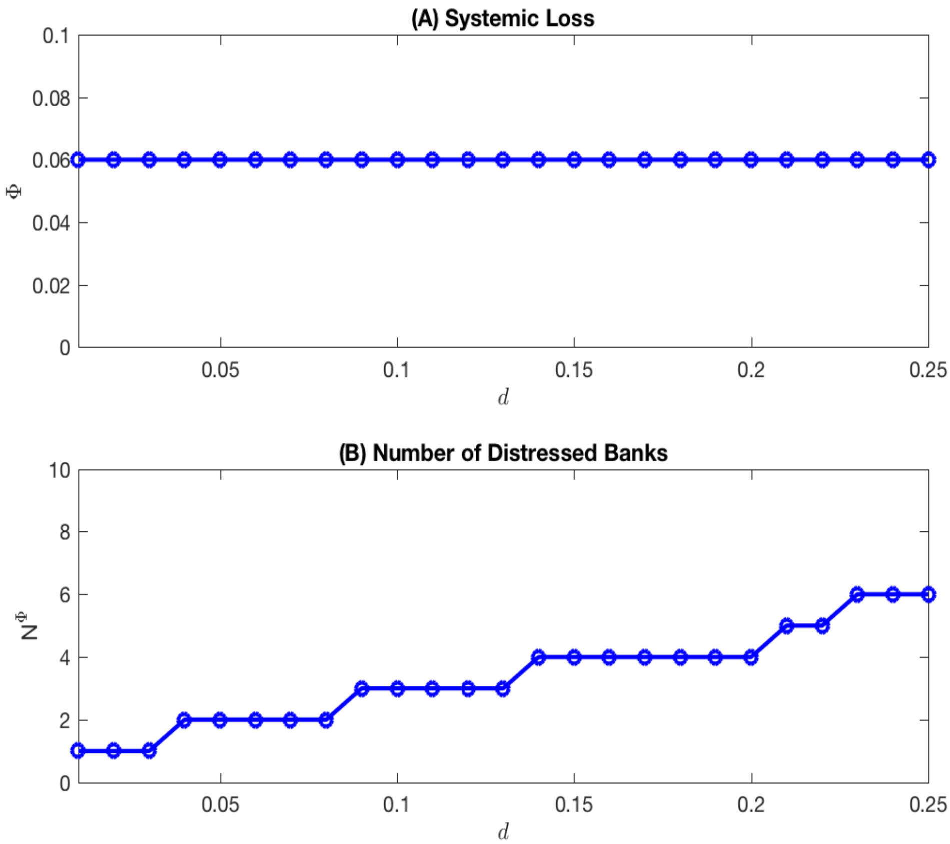


FIGURE 3.6: Impact of interconnectedness on systemic liquidity risk. The simulation runs using parameters in Table 3.1 with varying network density values. Φ is the systemic loss due to liquidity hoarding, N^{Φ} is the number of distressed banks and d is density. The result is based on the average of 100 simulations.

Next, we assess the impact of interconnectedness in the interbank market on the propagation of systemic risk within the system. We use density as shown by Equation 3.3 as a measure of interconnectedness of the interbank network. The value of the network density in the benchmark scenario is calibrated to be 0.15. Here, we explore the dynamics of the model over a range for density from 0.01 to 0.25, while using the same values of other parameters as in the benchmark model.

Figure 3.6 shows the results of this exercise. As can be seen form Panel (A) the value of systemic risk seems to be unaffected by the level of connectivity within the interbank market. This finding might seem counterintuitive at first sight given numerous studies that confirm the role of interconnectedness in systemic risk propagation (see e.g. Eisenberg and Noe, 2001; Furfine, 2003; Freixas et al., 2000; Allen and Gale, 2000). However, this might be justified by considering that systemic risk is measured as the system wide loss due to liquidity shortage at some banks which results from elevated margin calls. These margin calls originate in the OTC derivatives market and are not affected by the degree of connectivity in the interbank market. Nevertheless, interconnectedness in the interbank market affects the number of distressed banks as shown in Panel (B). At higher levels of connectivity, when a bank decides to withdraw funding it affects more banks and the same level of systemic liquidity loss is divided between a larger number of banks. This explains why systemic loss is not affected while the number of distressed banks increases with density.

In addition, the results shown here highlights another adverse impact of interconnectedness on bank risk. It is widely argued that interconnectedness affects counterparty credit risk either through concentration of exposures or through boosting default propagation in dense networks. Nevertheless, as we show here, interconnectedness can also affect liquidity risk adversely through its impact on the propagation of liquidity distress within the interbank market network. Banks, thus, need to take a proactive approach to liquidity risk management by actively monitoring interconnectedness on an ongoing basis. But given that interconnectedness cannot be observed by a single bank as it requires mapping all counterparties data to identify and illustrate overall exposures, there is a need for a system regulator to monitor any concentration of risk that might result in unexpected losses. Still, a bank needs to ensure that it has accurate and reliable data about its own counterparties to ensure it becomes aware of any areas in which interconnectedness is introducing more risk than expected. A bank can then adjust its reserves and change its strategy while there is still time before being hit by liquidity distress from other banks.

3.6.5 Impact of Haircut

In this exercise, we assess the impact of haircut rates on the propagation of systemic liquidity risk in the interbank market. The dynamics in systemic risk in this case results from the change in the average haircut that a bank might be subject to when selling less liquid assets to fund a margin call. The average haircut includes both the system wide haircut and the average bank-specific haircut $\alpha + \bar{\alpha}_i$. Here, we explore the dynamics of the model over a range for the haircut from 0.01 to 0.10, while using the same values of other parameters as in the benchmark model.

The results are shown in Figure 3.7. Panel (A) shows that systemic risk is negligible for a haircut set at low level. It then increases with the increases in the haircut level, and finally converges to a level similar to those obtained in the benchmark model. Recall that a distressed bank has two options to fund a margin call: interbank liquidity withdrawals and selling less liquid assets. The decision of selecting one option over the other depends on the comparison between the cost of liquidity hoarding γ and the average total haircut $\alpha + \bar{\alpha}_i$. Given that the maximum cost of liquidity hoarding γ is set to be 0.05, a distressed bank will sell

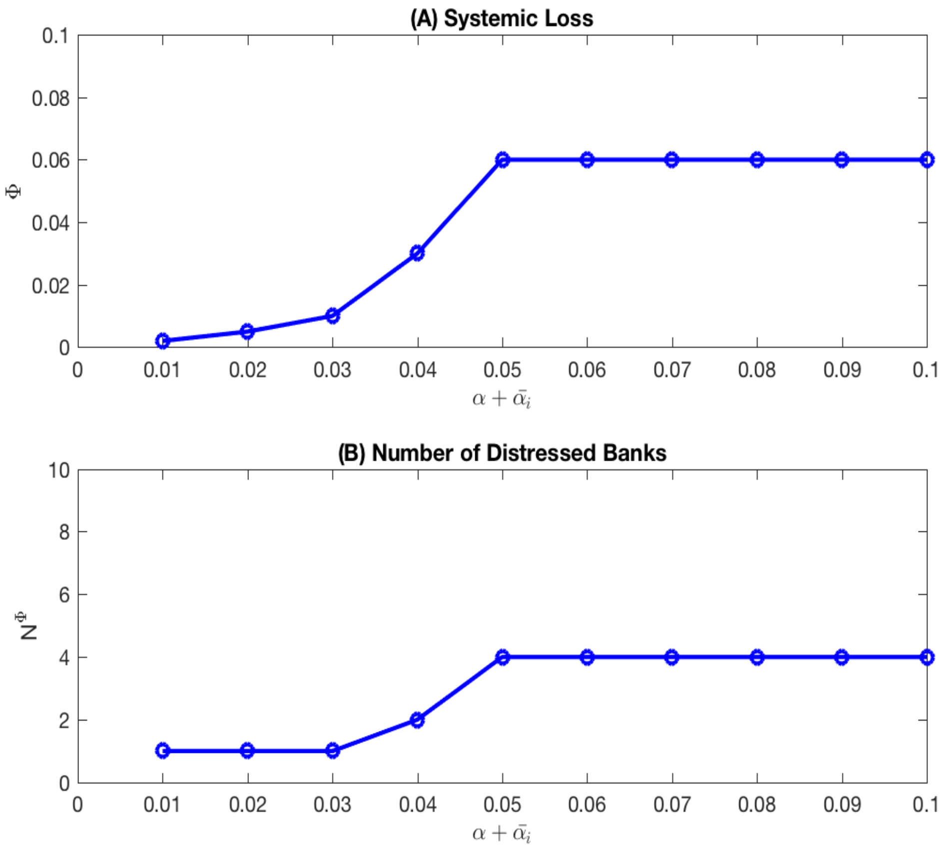


FIGURE 3.7: Impact of haircut on systemic liquidity risk. The simulation runs using parameters in Table 3.1 with varying haircut values. Φ is the systemic loss due to liquidity hoarding, N^{Φ} is the number of distressed banks and $\alpha + \bar{\alpha}_i$ is the total haircut. The result is based on the average of 100 simulations.

less liquid assets as long as $(\alpha + \bar{\alpha}_i) < 0.05$. Beyond this threshold, a distressed bank finds it less costly to hoard liquidity from the interbank market with a cost that is capped at 0.05 as in the benchmark model. The same notion is confirmed in Panel (B). The number of distressed banks increases with the the increase in haircut as more banks would now withdraw liquidity from the interbank market leading other banks to become distressed.

The findings shown in this section provide some insight into the role of liquidity provider of last resort. In distress times, a central bank may stand ready to act as a temporary market maker of last resort by providing low haircut rates for banks willing to fund their liquidity needs. The aim would be to improve the liquidity of distressed banks and limit the spillover of distress to other market participants. Also, these findings have some implications at the bank level. An effective liquidity risk management framework should consider the possibility and expected levels of haircuts during distress times. This implies that banks should ensure that their holdings of liquid assets are of sufficient quality to limit the possibility that they would be subject to high levels of haircuts in times of financial distress. In addition, the impact of haircuts should be adequately accounted for when setting liquidity coverage targets.

3.6.6 Sensitivity Analysis

The effect of margin procyclicality on systemic liquidity risk depends on some modelling assumptions. In this section, we explore how the implications for distress spillover from the OTC derivatives market to the interbank market change when we modify some assumptions of the benchmark model.

3.6.6.1 Liquidity Hoarding Multiplier

The liquidity hoarding multiplier λ is used to capture the average level of panic in the interbank market. In the benchmark model we assumed that banks hoard liquidity only to the extent that covers their liquidity needs in the OTC derivatives market. However, the interbank market has witnessed times of a lending freeze and high levels of liquidity hoarding during the financial crisis of 2008 (van den End and Tabbae, 2012). Thus, it is reasonable to assume higher levels for λ. We run another simulation to explore the dynamics of systemic risk using a range of $\lambda \in [1, 3]$. The results are shown in Figure 3.8. Both systemic loss and the number of distressed banks increase with the increase in λ. This result confirms the notion that when uncertainty increases in the interbank market banks hoard larger amounts of liquidity which leads to more panic and increases the number of banks that become distressed.

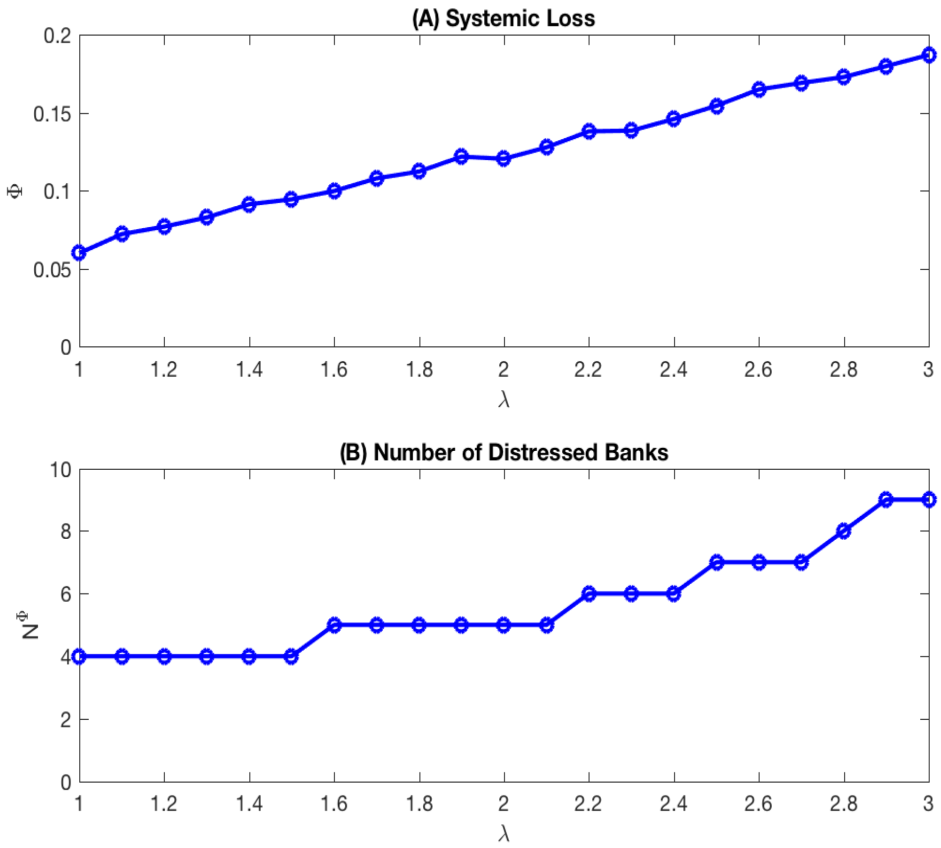


FIGURE 3.8: Sensitivity analysis of the liquidity hoarding multiplier.The simulation runs using parameters in Table 3.1 with varying liquidity hoarding multiplier values. Φ is the systemic loss due to liquidity hoarding, N^{Φ} is the number of distressed banks and λ is the liquidity hoarding multiplier. The result is based on the average of 100 simulations.

3.6.6.2 Modified Duration

In our model, market interest rate change is assumed to be common across all the derivatives contracts. It cannot be hedged or diversified away and lead to changes in the contract value. The sensitivity of a derivatives contract to changes in market interest rates is approximated by β as illustrated by Equation 3.8. In our baseline calibration, we set $\beta = 2$. However, it is entirely possible that real values of β can be lower or higher than this value. We run another simulation to explore the dynamics of systemic risk using a range of $\beta \in [0, 3]$. The results are shown in Figure 3.9. As illustrated, systemic risk is limited at low levels of β. Nevertheless, both systemic loss and the number of distressed banks increase with further increases in β. This result confirms the notion that higher sensitivity leads to higher changes in the derivatives contract value which in turn results in higher margin calls. The elevated margin calls make more banks vulnerable to liquidity shortage and increases systemic loss.

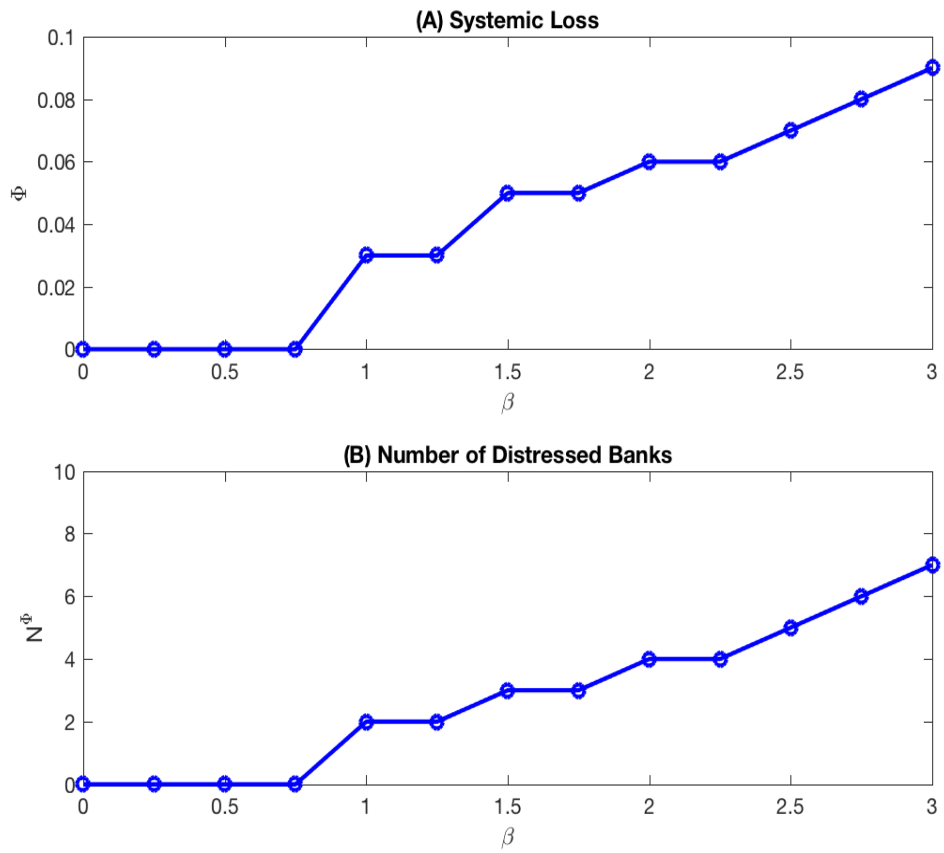


FIGURE 3.9: Sensitivity analysis of the derivatives contract value sensitivity to changes in market interest rates. The simulation runs using parameters in Table 3.1 with varying modified duration values. Φ is the systemic loss due to liquidity hoarding, N^{Φ} is the number of distressed banks and β is the measure of modified duration. The result is based on the average of 100 simulations.

3.7 Conclusion

In this chapter, we analyze the distress spillover from the OTC derivatives market into the interbank market. We focus on the impact of margin procyclicality in the OTC derivatives market on systemic liquidity risk in the interbank market. Our work brings together the micro-structure and the macro-structure of these markets within a quantitative framework to show how market volatility would lead to contagion among market participants. In so doing, we focus on a specific question that has recently risen to the top of policy agendas: how does margin requirements coupled with interbank propensity for liquidity hoarding affect the systemic risk propagation in a financial network of banks?

Given that the model reproduces the qualitative features of the data, we use it to investigate some of the policy implications of margin requirements. To this end, the general approach followed is to perturb the OTC derivatives market with an interest rate shock and analyse the systemic risk propagation within the interbank market. The model demonstrates that margin procyclicality derived by interest rate volatility can lead to the onset of a systemic liquidity shortage within the interbank market. It also shows that central clearing might in fact increase the possibility of a systemic liquidity crisis due to tight margin requirements. Consistent with previous evidence, the model predicts that interconnectedness amplifies the effect of systemic risk. The model also shows that haircut levels affects the possibility of a systemic liquidity crisis, and highlights the potential role of a market maker of last resort in limiting this possibility.

Overall, the results of this chapter illustrate the tension between the micro-level decisions of individual banks and the macro-level outcomes of these decisions. During stress time, banks make decisions about their interbank lending that are rational from each individual bank perspective. However, from a systemic perspective, these decisions generate undesirable results. A decision of a single bank to hoard liquidity in the interbank market might spread the liquidity hoarding contagion to other banks causing systemic loss. This systemic loss results from the cost of liquidity withdrawals of interbank lending which are endogenously driven by bank's propensity for liquidity hoarding during distress times. This contagion dynamic is thus characterised by a self fulfilling process among banks.

Our model is the first attempt to analyse the effects of margin requirements on systemic liquidity risk. Since the model is stylised, it abstracts from some important factors that could affect our conclusion. For instance, the model does not consider the possibility that selling less liquid assets could lead to a fire sale and distress asset prices. Also, we consider only one type of derivatives contracts, and thus it is not straightforward to generalise the results to all types of OTC derivatives exposures. Nevertheless, the work presented here can be extended in different ways. For example, different structures of the financial network can be investigated to explore the effect on systemic risk propagation. Also, it would be helpful to investigate the extent to which a bank is subject to margin procyclicality based on its risk aversion which plays an important role in the direction of its trades. Finally, another extension may involve the effects of banks' balance sheet heterogeneity on the systemic risk propagation.

Chapter 4

Macroprudential Stress Testing of Bank Liquidity and Solvency

Chapter 4: Macroprudential Stress Testing of Bank Liquidity and Solvency [1]

Abstract:

We develop a macroprudential stress test which integrates bank's liquidity and solvency risks, and estimates the change in both based on the evolution of financial distress within the banking system. We estimate this evolution of financial distress using a new measure of systemic distress that incorporates idiosyncratic and systemic risks in the banking system network. We apply the stress test framework to the U.S. banking system and identify the systemic vulnerability of individual banks and the resilience of the system as a whole to economic risks. We also use this framework to identify and monitor systemic interdependencies between banks.

Keywords: Solvency; Liquidity; Macroprudential Policy; Stress Testing; Systemic Risk; Networks

JEL Classification: G01; G21; G28

[1]This chapter has been submitted in November 2017 to the *Journal of Money, Credit, and Banking* and is currently under review for publication.

4.1 Introduction

The financial crisis of 2007-2008 has revealed the need for better macroprudential policy in order to limit systemic risk and to enhance financial stability. It is widely accepted in the literature that systemic risk is the main threat to financial stability. Impairment of financial stability can impose significant costs on the real economy in terms of economic growth and social welfare. Thus, to protect the real economy from the financial system, it is necessary to detect and to gauge potential sources of systemic risk emerging at the system level. Meanwhile, to protect the financial system from the real economy, it is necessary to assess the robustness of the financial system to macroeconomic shocks. To this end, macroprudential stress tests have been established as the main tool of macroprudential policy (Tarullo, 2016).

The current practice of macroprudential stress testing has improved in the aftermath of the financial crisis. However, the underlying techniques and models that have been developed prior to the crisis have remained broadly the same and there are still some limitations that need to be addressed (Borio, Drehmann and Tsatsaronis, 2014). In particular, a recent report from the Basel Committee on Banking Supervision (BCBS) highlights two main limitations, namely considering liquidity and solvency interactions and considering systemic risk (Basel Committee on Banking Supervision, 2015). The International Monetary Fund (IMF) provides a similar recommendation in its 2014 Review of the Financial Sector Assessment Program (FSAP). The review stresses the need to strengthen the systemic focus of the financial stability assessment and to deepen the analytical treatment of interconnectedness (IMF, 2014).

In this chapter, we develop and illustrate with an empirical application an integrated macroprudential stress test of bank liquidity and solvency risk. The proposed approach introduces, with the use of network theory, a new measure of systemic distress that incorporates microprudential as well as macroprudential risks in the banking system network. Our proposed approach integrates liquidity risk and solvency risk and provides a convenient method to identify the point at which liquidity risk becomes solvency risk. In addition, the proposed stress testing framework is flexible as it allows the stress tester to further use different stress scenarios to assess the impact of liquidity shocks on solvency and vice versa. The framework also provides a variety of output metrics that capture idiosyncratic as well as systemic economic risks at the level of an individual bank and the banking sector as a whole. Yet, the framework is tractable enough to be useful for practical macroprudential monitoring and informative for policy-making.

An important strength of our approach is that it explicitly links liquidity risk and solvency risk in order to incorporate their interactions in the stress testing framework. These interactions have often been neglected in existing stress-testing methodologies. We create this link by estimating both the probability of a bank becoming illiquid and the probability of a bank becoming insolvent based on the same factor, namely the bank's distress level. We estimate these probabilities using a Merton-type model that is based on the seminal work of Black and Scholes (1973) and Merton (1974). In so doing, we assume that bank distress is a continuous state with varying levels that depend on both idiosyncratic and systemic risks of each bank, whereas, illiquidity and insolvency occur at specific points of highly elevated distress. The higher the distress level of a bank the closer it gets to its illiquidity and insolvency points.

Another important strength of our approach is the way in which we incorporate interconnectedness between banks into the stress test design. Given that our purpose is assessing the vulnerability of banks, it is more appropriate to focus on a bank's systemic distress as compared to its systemic importance. We approximate a bank's systemic distress using a novel measure named *DistressRank*. This measure fully incorporates the interbank network topology. It is based on the notion that the distress level of a bank is a function of its idiosyncratic risk as well as its systemic risk stemming from being connected to counterparties through interbank assets or liabilities. DistressRank also captures the dynamics on the network as it changes with the change in banks' distress level.

We construct stress scenarios in two different ways, where the first is designed to assess the resilience of the banking system to macroeconomic shocks, and the second is designed to assess the possibility of amplifying endogenous shocks within the banking system and transmitting them to the macroeconomy. The empirical application of the stress test framework to the U.S. banking system shows how it can be effectively used to identify the systemic vulnerability of individual banks and the resilience of the system as a whole to economic risks. It also shows how the proposed approach can be effective for monitoring and assessing systemic interdependencies among banks. The proposed approach, thus, provides a tool for the banking system supervisors to analyse the current state of the system stability and to monitor the evolution of contagion and systemic risk within the system.

Our findings point out the importance of considering interconnectedness in designing macroprudential stress tests. At the system level, the systemic loss due to feedback loops is shown to be significant compared to the direct loss that results from the initial shock to the system. Ignoring these feedback effects may lead to a significant underestimation of systemic loss. At the bank level, the results confirm that interlinkages play a significant role in identifying individual banks vulnerability. On this premise, we use DistressRank as a measure of a bank's systemic distress. The results show that a bank's DistressRank is associated with its systemic feedback loss.

Our findings also provide insights into the possibilities of distress propagation within the system. Applying the proposed framework to the U.S. banking system enables us to identify banks that are most vulnerable to system-wide shocks. In addition, we identify the liquidity distress dependence and solvency default dependence between banks in the system. A striking finding that is shown here is that banks that are not directly connected through interbank assets or liabilities are still subject to distress from each other through *common counterparties*.

The remainder of this chapter is organised as follows. Section 4.2 provides an overview of macroprudential stress testing in the literature. Section 4.3 develops an initial model for illiquidity distress propagation. Section 4.4 extends the model to link illiquidity to insolvency. Section 4.5 introduces a framework for an integrated macroprudential stress test of liquidity and solvency risk. Section 4.6 provides an overview of the data used in this chapter and presents the results of performing the stress test. Section 4.7 concludes the chapter.

4.2 Related Literature

We develop our stress testing framework based on a balance sheet setting which is the natural approach to macroprudential stress testing. This approach is specially useful in cases of limited or poor market data availability, as the main data required for the test is extracted from banks' balance sheets (Ong and Čihák, 2014). Early models under this approach provide a framework for an aggregate stress test of the financial system (e.g. Blaschke et al., 2001; Bunn et al., 2005), however, they are fundamentally financial simulations with no formal links to the macroeconomy (Buncic and Melecky, 2013). More recent models attempt to establish this link by using satellite models to link the macroeconomic variables to bank's asset quality (Čihák, 2007). A more sophisticated, yet tractable, accounting-based stress test is introduced by Drehmann et al. (2010), in which they model assets and liabilities simultaneously. This model integrates credit and interest rate risk in the banking book and provides a framework to assess the impact of different investment strategies on the bank's profitability. Nevertheless, it is worth noting that the quality of any analysis that follows a balance sheet approach to stress testing depends on the granularity and availability of the data. Some models attempt to overcome this limitation and provide sophisticated techniques to perform stress testing in cases of limited data (e.g. Segoviano and Padilla, 2006; Ong, Maino and Duma, 2010).

In theory, liquidity and solvency risks interact and can cause each other through the interactions between banks (Diamond and Rajan, 2005). However, empirical evidence on the nexus between liquidity and solvency risks is scarce. Some studies have strived to establish the link between liquidity and solvency in order to be incorporated into macroprudential stress tests. In particular, Schmitz, Sigmund and Valderrama (2017) suggest that bank funding costs are correlated with bank capital as a result of the interconnections between funding costs and market expectations about bank solvency. Other studies suggest a significant impact of solvency on bank funding costs (Hasan, Liu and Zhang, 2016), which appears to be nonlinear with higher sensitivity of funding cost at lower levels of bank solvency (Aymanns et al., 2016). The relationship seems to be intuitive when we consider the interactions between liquidity and solvency. When a bank faces a liquidity shortage, it might be forced to sell its less liquid assets. If other banks with similar conditions follow the same way of selling less liquid assets, the initial liquidity shortages may lead to fire sales and consequently declines in asset prices, hence, causing solvency problems (Lee, 2013). Similarly, concerns about bank insolvency can cause liquidity shortages. Increased expectations about a bank insolvency (e.g. declines in credit rating) can increase deposits withdrawal and interbank funding costs as depositors and interbank counterparties, respectively, become less confident about the bank creditworthiness, hence causing a liquidity shortage for the bank (Pierret, 2015). Thus, propagation channels between liquidity and solvency are common and, for macroprudential purposes, they should be integrated within a unified stress testing framework. However, the focus of macroprudential stress testing frameworks has usually been on solvency risk, while liquidity risk is assessed using satellite models on a stand-alone basis.

Our proposed methodology is closely related to the Macrofinancial Risk Assessment Framework (MFRAF) that has been developed by the Bank of Canada and integrates solvency and liquidity risk (Gauthier, Souissi et al., 2012). In the framework, solvency risk is triggered by a macro shock, whereas liquidity risk arises as a result of solvency concerns or deterioration in liquidity position. We use a similar framework that considers potential market liquidity risk and interbank counterparty credit risk through a network model. Another macroprudential stress testing model that integrates solvency and liquidity risk has been developed by the Hong Kong Monetary Authority (Wong and Hui, 2009). Our methodology shares some characteristics with this model with regard to combining elements of balance sheet-based and market price-based approaches to stress testing. In this model, solvency risk of an individual bank depends on the market value of its total assets, calculated through a Merton-type model. In contrast, we estimate solvency and liquidity risks based on the volatility of liquid assets instead of total assets. In this model, liquidity risk is assessed by introducing an exogenous shock to asset prices which leads to increases in the bank's solvency risk and deposit outflow, and reduction in its liquidity generation capability.

Our approach rests on the insight of the Merton-type models of default risk that are based on the seminal work of Black and Scholes (1973) and Merton (1974). In these models, equity of the firm can be viewed as a call option held by owners on its total assets, where the strike price is equal to the outstanding debt owed to creditors at maturity. In this context, a market-implied probability of default can be estimated as the probability that the market value of the firm's assets falls below the book value of its liabilities Bohn and Crosbie (2003). We use the same logic to estimate two types of probabilities for each individual bank, namely the probability of illiquidity and the probability of insolvency. We deviate, however, from the standard approach in that we base the estimation of both probabilities on liquid assets only instead of total assets. Our rationale is that, in the short run the variability in assets is derived mainly by the variability of liquid assets. This twist enables us to link liquidity and solvency risks directly as both of them are estimated based on the same factor.

Our methodology is also related to the Contingent Claims Analysis (CCA) that relies on a Merton-type framework to construct a risk-adjusted balance sheet of individual banks (Gray and Malone, 2008; Gray and Jobst, 2010). The CCA model can be used for macroprudential stress testing by applying a macroeconomic shock to the risk-adjusted balance sheet of individual banks and then estimating the change in banks' market value of equity and probability of default. However, the CCA model limits its focus to solvency risk and lacks the systemic view as it does not provide a method to measure aggregated risk at the system level. Our methodology also shares some characteristics with the distress dependence model of (Segoviano and Goodhart, 2009) who investigate the effect of macroeconomic variables on bank losses where the joint probability distribution of banks is constructed with Copulas. They model the financial system as a portfolio of banks and use non-parametric statistical techniques to construct a multivariate density function for the financial system. Then, they estimate a joint probability of default and a banking stability index of the whole banking system.

We base our stress test on a network model that provides a convenient way to incorporate systemic risk and interconnectedness into the stress testing framework. Early studies of financial contagion suggest that financial networks can provide a better way to study the linkages among financial institutions (e.g. Allen and Gale, 2000; Freixas, Parigi and Rochet, 2000). More recent studies support the same notion and emphasise that financial networks can help provide better measurement of systemic risk and financial instabilities (e.g. Gai, Haldane and Kapadia, 2011; Gai and Kapadia, 2010; Glasserman and Young, 2015; Elliott, Golub and Jackson, 2014; Acemoglu, Ozdaglar and Tahbaz-Salehi, 2015; Glasserman and Young, 2016). In this spirit, we depict the relationships within the banking sector as a network in which banks represent the nodes and financial exposures represent the edges between these nodes. This approach to studying the financial markets, in general, enables us to better understand the interconnectedness and the propagation of distress. This is also the approach followed by some regulatory (e.g. Gauthier, Souissi et al., 2012; Wong and Hui, 2009; Sole and Espinosa-Vega, 2010) and academic (e.g. Gauthier, Lehar and Souissi (2012) and Levy-Carciente et al. (2015)) stress testing frameworks. Sole and Espinosa-Vega (2010) use a network setting to simulate the impact of credit and funding shocks on a set of connected banking systems. Levy-Carciente et al. (2015) use a bipartite bank-asset network to design a solvency stress test of the Venezuelan banking system. Gauthier, Lehar and Souissi (2012) use a network model to estimate a bank's macroprudential capital requirements as a function of its contribution to the system-wide risk.

4.3 Illiquidity Distress

This section provides a simple model of liquidity risk, where we use a balance sheet approach to derive a measure of systemic illiquidity distress of a bank in a financial system.

4.3.1 A System of Networked Balance Sheets

We model an interbank market that consists of a number of banks $N \in \{1, ..., N\}$. The assets of each bank are divided into liquid assets and illiquid assets denoted as A_i^L and A_i^F, respectively. In addition, the liabilities of each bank consist of short term obligations denoted as L_i^S, and long term obligations denoted as L_i^F. The net worth of bank i is E_i and is equal to the difference between its total assets and its total liabilities. Thus, the balance sheet identity of bank i can be represented as:

$$A_i^L + A_i^F = L_i^S + L_i^F + E_i \tag{4.1}$$

Furthermore, we differentiate between two sources of liquid assets, namely interbank liquid assets and other liquid assets denoted as A_i^B and A_i^O respectively, where $A_i^L = A_i^B + A_i^O$. Similarly, the short term obligations are divided into interbank short term obligations, L_i^B, and other short term obligations, L_i^O, where $L_i^S = L_i^B + L_i^O$. The interbank liquid assets and short term obligations represent assets and liabilities originating from the interbank market (e.g. interbank repo or derivatives transactions), whereas other liquid assets and other short term obligations are not related to the interbank market and might include cash or short term securities.

The separation of interbank liquid assets and short term obligations enables us to model the liquidity interlinkages across banks in the interbank market as a weighted directed graph whose vertices represent banks and edges represent interbank assets and liabilities. The assets, in monetary units, of bank i with bank j is denoted by A_{ij}, which represents the amount that bank i should receive from bank j as a result of some financial transaction (e.g a derivatives contract). Similarly, the interbank liabilities of bank i to bank j is denoted by L_{ij}, which represents the amount that bank i should pay to bank j. It then follows that, the interbank liquid assets of bank i are given by $A_i^B = \sum_{j=1}^N A_{ij}$, whereas the interbank liabilities of bank i are given by $L_i^B = \sum_{j=1}^{N} L_{ij}$.

4.3.2 Liquidity Coverage Matrix

Banks use their stock of liquid assets to cover their own liquidity requirements. Thus, we can define a *liquidity coverage ratio* for a bank i as:

$$\ell_i = \frac{A_i^L}{L_i^S} \tag{4.2}$$

which measures the ability of bank i to meet its short term obligations, whether within the interbank market or to outside counterparties. The higher the liquid assets as compared to short term obligations, the higher the liquidity coverage ratio, and the more liquid the bank is.

Furthermore, in order to measure the ability of bank i to cover its obligation to another counterparty j within the interbank market, we introduce ℓ_{ij} as the bank i's *relative liquidity coverage ratio* to bank j, where:

$$\ell_{ij} = \frac{[A_i^L - L_i^S] - A_{ij} + L_{ij}}{L_{ij}} \tag{4.3}$$

This ratio represents the ability of bank i to cover its interbank obligation to bank j using its net liquidity $(A_i^L - L_i^S)$, after paying all other obligations and before exchanging any liquidity with bank j. This is why we adjust the net liquidity stock of bank i in the numerator by subtracting the liquidity exposure that is owed to bank i by bank j and adding back the liquidity exposure owed to bank j by bank i, to reflect a case before exchanging liquidity.

4.3.3 Illiquidity Distress Matrix

It is clear from Equation 4.2 and Equation 4.3 that the better the liquidity position of a bank as measured by its liquidity coverage ratios, the lower the threat of distress due to illiquidity that the bank is exposed to. It is also worth noting that ℓ_{ij} provides a proxy to the relative vulnerability of bank j to the liquidity distress that might arise at bank i. In other words, the lower this ratio is, the higher the probability that bank i will fail to honour its obligation to bank j, and the higher the vulnerability of bank j.

We use this notion to develop an illiquidity distress matrix defined as $\mathbf{D} = [d_{ij}]$, where an element d_{ij} represents the relative vulnerability of bank i to the illiquidity distress of bank j, in other words the contribution of bank j to the vulnerability of bank i. We then define d_{ij} as:

$$d_{ij} = \frac{a_{ij}}{\ell_{ji}} \tag{4.4}$$

where a_{ij} is the respective element from the adjacency matrix $\mathbf{A}$ of interbank network which is defined as $\mathbf{A} = [a_{ij}]$, where $a_{ij} = 1$ if banks i and j are connected and $a_{ij} = 0$ otherwise.

4.3.4 DistressRank: A Measure of Systemic Distress

The network literature suggests that the centrality of a node in a given network is a function of its interconnection with its neighbours. One method to quantify this centrality is a measure called *eigenvector-centrality*, which is based on the notion that the centrality of a node is proportional to the sum of centralities of its neighbours (Newman, 2010*a*). Applying this notion to our financial network results in:

$$c_i = \frac{1}{\lambda} \sum_{j=1}^{N} a_{ij}\ c_j \tag{4.5}$$

where c_i is the eigenvector centrality of bank i, $\lambda \neq 0$ is a constant. Thus, the eigenvector centrality can provide a relative ranking of banks. One advantage of this method is that it bases the ranking on both local information related to direct neighbours and global information of the network given that the ranking of neighbours is based on the ranking of their neighbours, and so on (Scott, 2017).

However, eigenvector centrality is a purely topological measure that is solely based on the adjacency matrix **A**. This limitation renders it subject to two main disadvantages when it comes to ranking banks in a financial network. First, it assumes equal contribution of all exposures in the network in determining the centrality of a given bank. This assumption is not valid as it ignores the state of the bank's counterparty, i.e. its distress level. A bank is more vulnerable to banks with high distress levels compared to other banks. Second, eigenvector centrality ignores the dynamics in the network as it is based on the mere existence of an exposure between two banks rather than the weight of this exposure. Hence, it is time-independent as it does not change in response to changes in the weights of exposure or the states of banks.

Therefore, we propose *DistressRank* as an improvement on the standard eigenvector centrality to overcome the disadvantages mentioned above. To this end, we estimate DistressRank based on the distress matrix **D**, which was introduced in Equation 4.4. Let ρ_i be the DistressRank of bank i, which can be defined as:

$$\rho_i = \frac{1}{\lambda} \sum_{j=1}^{N} d_{ij} \ \rho_j \tag{4.6}$$

where $\lambda \neq 0$ is a constant. With some rearrangements, Equation 4.6 can be rewritten in matrix notation as:

$$D \cdot \rho \ = \ \lambda \cdot \rho \tag{4.7}$$

which is a standard eigenvector-eigenvalues problem where λ is an eigenvalue and ρ is its corresponding 1 x N vector. Given that the matrix **D** is non-negative and

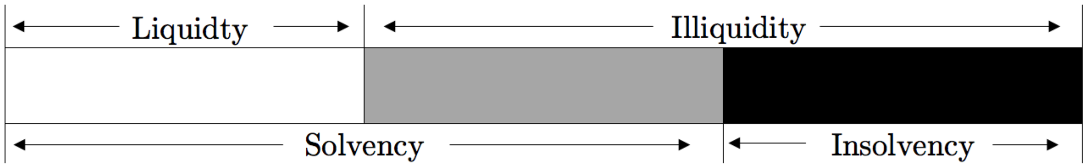


FIGURE 4.1: From illiquidity to insolvency. The white area represents a healthy bank that is both liquid and solvent. The grey area represents a stage in which the bank has become illiquid, yet still solvent. The black area represents the stage in which the bank has become both illiquid and insolvent.

according to the Perron-Frobenius theorem (Meyer, 2000), the above eigenvector-eigenvalues problem has a unique solution at $\lambda = \lambda_{max}$. In other words, only the largest eigenvalue λ_{max} results in the desired non-negative eigenvector ρ which represents the DistressRank vector of banks where the i^{th} entry corresponds to the DistressRank of the i^{th} bank. Equation 4.7 can be solved iteratively using the power iteration method (Newman, 2010*a*).

DistressRank is more suitable as a measure of systemic distress of a bank in a financial network because it assigns a rank to each bank in the network based on the distress of its counterparties. Thus, it is more suited to be used with dynamic networks where the states of banks and the weights of exposures change during a distress propagation process. Here, we use DistressRank as one of the main metrics in our macroprudential stress test that is introduced in Section 4.5.

4.4 Illiquidity and Insolvency

Assessing at what point liquidity risk becomes solvency risk is, at best, difficult. In this section, we attempt to disentangle these two risks, and show how to express solvency risk in terms of liquidity risk.

4.4.1 From Illiquidity to Insolvency

Typically, a bank i is considered *illiquid* when $A_i^L \leq L_i^S$, in other words, when the market value of its liquid assets is less than the face value of its short-term obligations. The same logic can be extended to insolvency. A bank is considered *insolvent* when the market value of its assets falls below the face value of its obligations, where $E_i \leq 0$.

Figure 4.1 illustrates the relation between illiquidity and insolvency. We would expect a bank to be liquid and solvent as shown by the white area in this figure. Nevertheless, a bank might become illiquid while still being solvent as shown by the grey area. However, If the bank's illiquidity problem is severe enough, it can lead to insolvency as shown by the black area in the same figure.

Another way to consider insolvency is by limiting the focus to liquid assets and short-term liabilities. Insolvency occurs when the decline in liquid assets is severe enough to exceed the value of equity. In other words, the bank becomes insolvent if the market value of its liquid assets deteriorates to the extent that the net change in its liquidity at a given time is larger than its equity. That said, we can introduce a new condition for insolvency in terms of liquid assets by which a bank is considered insolvent if:

$$E_i + \Delta A_i^L \leq 0 \tag{4.8}$$

where ΔA_i^L is the net change in the bank's liquidity position assuming that short term liabilities are valued at face value.

Thus, one might argue that, in the short-run, both illiquidity and insolvency can be measured in terms of the change in liquid assets, assuming that the change in illiquid assets is trivially small and liabilities are valued at book value. That said, the illiquidity point for a bank is defined to be the point at which $A_i^L = L_i^S$, as mentioned above. At the system level, the system-wide illiquidity point is the point at which $\sum_i A_i^L = \sum_i L_i^S$. At this point, we can estimate a system-wide liquidity coverage ratio, denoted as ℓ^L, that corresponds to the system-wide illiquidity point as :

$$\ell^L = \frac{\sum_i A_i^L}{\sum_i L_i^S} \tag{4.9}$$

Applying the same logic to insolvency, the insolvency point for a bank can be defined as the point at which $E_i = -\Delta A_i^L$, as shown by Equation 4.8. At the system level, it becomes straightforward that the system-wide insolvency point is the point at which $\sum_i E_i = \sum_i -\Delta A_i^L$. At this point, we can also estimate a system-wide liquidity coverage ratio, denoted as ℓ^S, that corresponds to the system-wide insolvency point as:

$$\ell^S = \frac{\sum_i A_i^L - \sum_i E_i}{\sum_i L_i^S} \tag{4.10}$$

where $\sum_i E_i$ represents the amount of liquid assets that, if depleted, the system is considered to have reached the insolvency point.

4.4.2 From Insolvency to Illiquidity

One way to measure insolvency risk is to determine how far away a bank is from insolvency. This approach is called distance-to-default, which is developed based on the structural model of corporate debt introduced by Black and Scholes (1973). On this premise, we drive a measure of insolvency risk for individual banks in our system. We call this measure *distance-to-insolvency* (δ^S) which is completely analogous to and based on the distance-to-default measure in the Moody's KMV model (see Bohn and Crosbie, 2003). However, unlike distance-to-default, we estimate the distance-to-insolvency using liquid assets and short term liabilities only, instead of total assets and total liabilities, assuming that the change in illiquid assets is trivially small and liabilities are valued at book value. The idea here is to identify how deep into illiquidity a bank can be before the condition in

Equation 4.8 is satisfied and the bank becomes insolvent.

The first step to estimate distance-to-insolvency of a given bank i, denoted as δ_i^S, is to identify the bank's insolvency point, which we derive from Equation 4.10 above. On average, the insolvency point of a bank i is $\ell^S L_i^S$. Thus, the distance-to-insolvency of bank i can be defined as:

$$\delta_i^S = \frac{ln\left(\frac{A_i^L}{\ell^S \ L_i^S}\right) + \left(\mu_{A_i^L} - \frac{1}{2}\sigma^2_{A_i^L}\right)T}{\sigma_{A_i^L}\sqrt{T}} \tag{4.11}$$

where $\mu_{A_i^L}$ and $\sigma_{A_i^L}$ are the mean and volatility of return on liquid assets, and T is the time horizon. It is worth noting from Equation 4.11 that distance-to-insolvency is simply the number of standard deviations that the bank is away from insolvency.

Furthermore, following the assumption in Black and Scholes (1973) that the random component of a firm's asset returns is normally distributed, we can define the *probability of insolvency* of a specific bank as:

$$\chi_i^S = N\left[-\delta_i^S\right] \tag{4.12}$$

where $N(x)$ is the cumulative distribution function (CDF) of the standard normal distribution $N(0,1)$. Notice also that χ^S is similar to the probability of default in standard credit risk models.

We now turn to estimating two measures of illiquidity risk; namely *distance-to-illiquidity* and *probability of illiquidity*. Needless to say, these two measures are analogous to those measures that we introduced above to measure insolvency risk. Thus, in order not to repeat ourselves, we just extend the same logic we used with insolvency. In so doing, we argue that illiquidity can be viewed as a special case of insolvency in the short-run, assuming that the change in illiquid assets is trivially small and liabilities are valued at book value.

To estimate the distance-to-illiquidity of a given bank i, denoted as δ_i^L, we start with identifying the average illiquidity point within the system which can be derived from Equation 4.9 as $\ell^L\ L_i^S$. It then follows that the distance-to-illiquidity of bank i is defined as:

$$\delta_i^L = \frac{ln\left(\frac{A_i^L}{\ell^L\ L_i^S}\right) + \left(\mu_{A_i^L} - \frac{1}{2}\sigma^2_{A_i^L}\right)T}{\sigma_{A_i^L}\sqrt{T}} \tag{4.13}$$

Similar to the distance to insolvency, we can interpret the distance to illiquidity as the number of standard deviations that the bank is away form illiquidity. Additionally, let χ_i^L be the probability of illiquidity for bank i. It follows that:

$$\chi_i^L = N\left[-\delta_i^L\right] \tag{4.14}$$

where $N(x)$ is the cumulative distribution function (CDF) of the standard normal distribution $N(0,1)$.

The relationship between the illiquidity and insolvency measures that we derive above can best be illustrated by Figure 4.2. Assuming a bank i that operates in a system with a system-wide illiquidity point (ℓ^L) and insolvency point (ℓ^S) of 100% and 50%, respectively. In panel (a), we estimate distance to insolvency (δ_i^S) and distance to illiquidity (δ_i^L), and in panel (b), the corresponding probabilities of insolvency (χ_i^S) and illiquidity (χ_i^L) over a range of liquidity coverage ratios (ℓ_i) from zero to 300%. The figure shows that as the liquidity coverage ratio decreases, both δ_i^L and δ_i^S decreases, while χ_i^L and χ_i^S increases in parallel. When ℓ_i reaches the illiquidity point of 100%, δ_i^L becomes zero, χ_i^L reaches 1, and the bank is considered to be illiquid. However, at the illiquidity point the bank is still solvent as δ_i^S is still higher than zero and χ_i^S is still lower than 1. As the bank sinks more into illiquidity, its δ_i^S moves towards the insolvency point and its χ_i^S converges to 1. At the insolvency point of 50%, δ_i^S becomes zero, χ_i^S reaches 1, and the bank is considered to be insolvent.

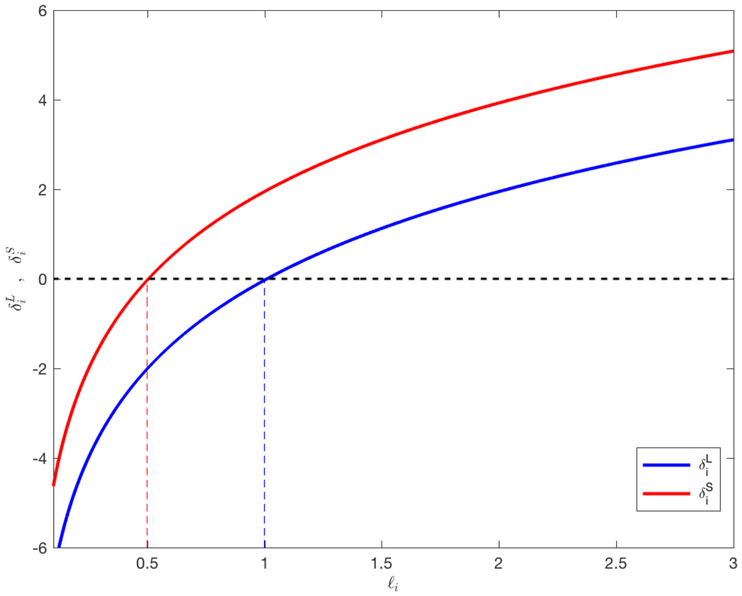
4.5 A Macroprudential Stress Testing Framework

In this section we provide a framework for a macroprudential stress test based on the measures that we introduced in Sections 4.3 and 4.4. This framework is illustrated in Figure 4.3. Also, in the subsections below, we outline this framework in terms of its inputs (distress scenario), process (distress propagation process) and outputs (DistressRank, Distress Dependence Matrix, Default Dependence Matrix, and Systemic Risk Matrix) .

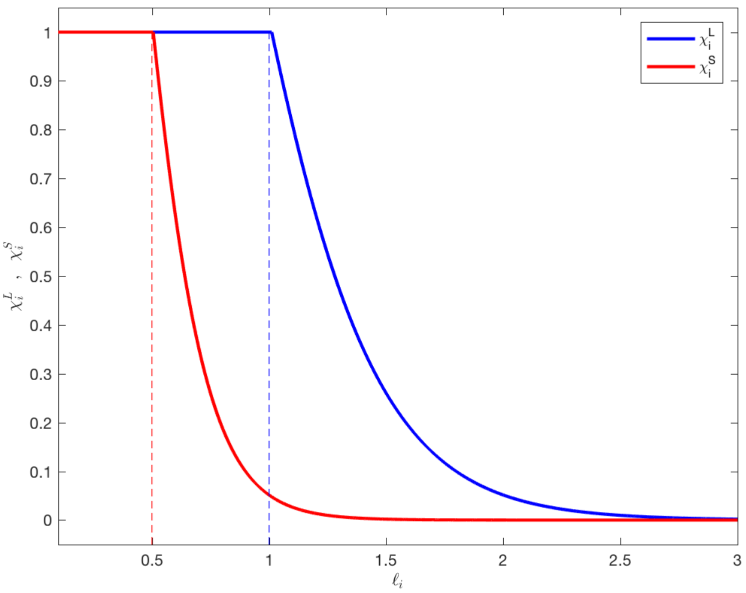
4.5.1 Inputs: Distress Scenario

The distress scenario in our framework refers to the set of shocks applied to individual banks, specific groups of banks or all banks in the system with the aim to examine the systemic impact and vulnerability of individual banks and the stability of the system as a whole. The framework is flexible to include any plausible set of shock events. However, we limit the analysis to two types of shocks, with each one designed to examine specific aspects of the stability of the system.

A- **The first scenario** involves applying a uniform shock to all banks in the system. The immediate effect of this shock is a proportional reduction in all banks' interbank assets leading to a reduction in liquidity positions. This scenario is also flexible to investigate the impact of a vector of heterogeneous shocks where each bank is affected differently.



(A) Distance to Illiquidity & Distance to Insolvency



(B) Probability of Illiquidity & Probability of Insolvency

FIGURE 4.2: The relationship between insolvency measures and illiquidity measures of a hypothetical bank i whose liquidity coverage ratio is denoted by ℓ_i. δ_i^L is the distance to illiquidity, and δ_i^S is the distance to insolvency. χ_i^L is the probability of illiquidity, and χ_i^S is the probability of insolvency. The system-wide illiquidity point (ℓ_i^L) and insolvency point (ℓ_i^S) are 100% and 50%, respectively.

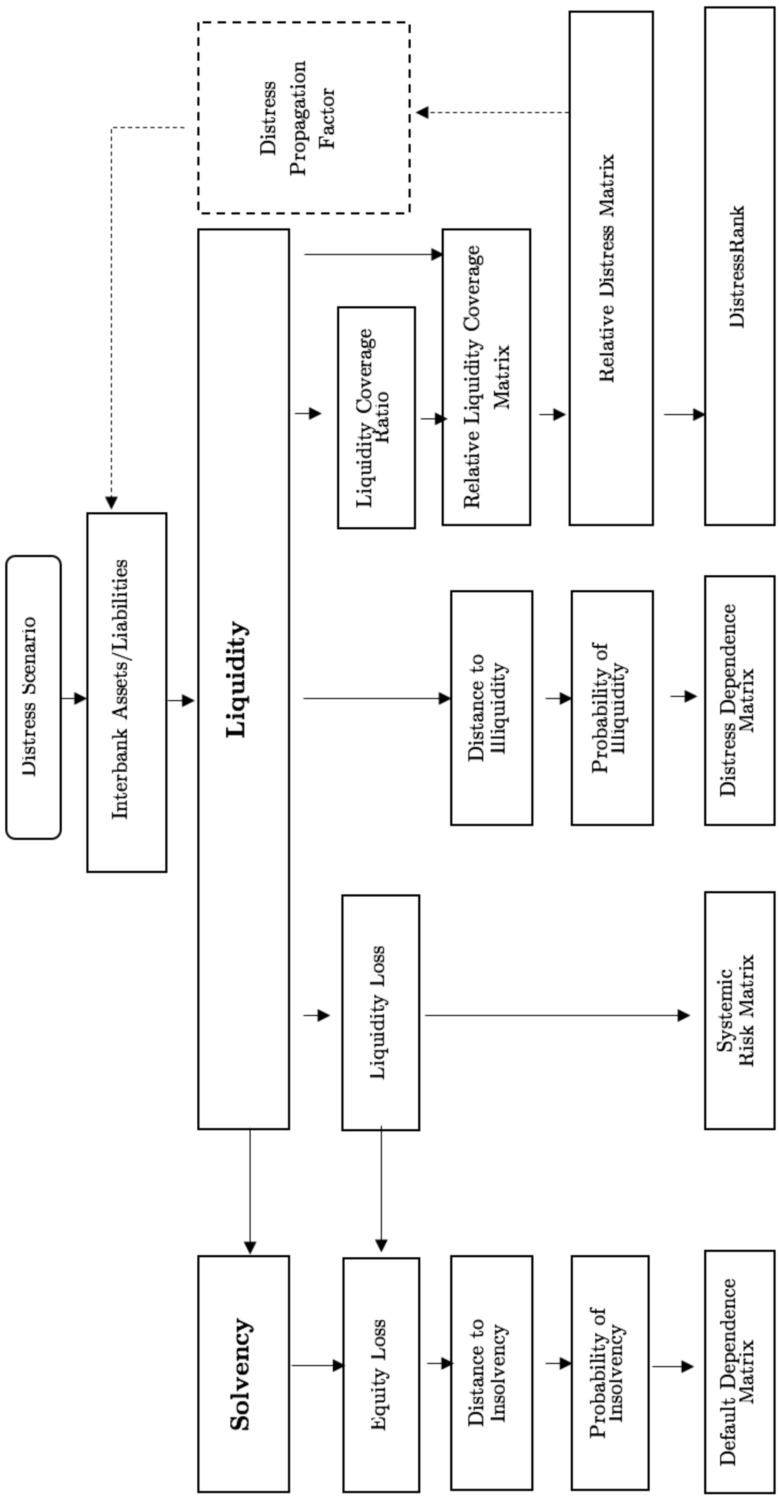


FIGURE 4.3: A framework for an integrated macroprudential stress test of liquidity and solvency.

B- **The second scenario** involves shocking banks sequentially. In each round a specific bank loses a given amount of its liquid assets and therefore becomes illiquid. The immediate effect of this shock is that the respective bank cross-defaults in all its interbank liabilities and accordingly the write-off of the interbank assets of its counterparties. This scenario is flexible to include a group of banks instead of a single bank.

The feedback round effects and final results of each scenario are explained in more detail in Sections 4.5.2 to 4.5.4, respectively.

4.5.2 Distress Propagation Process

The distress scenario that is developed in our stress test is assumed to unroll in two rounds:

A- **During the first round**, the initial effects of shocks to banks' liquidity positions are estimated by applying the shock to the respective bank or banks. The total initial impact of the shock is equal to the sum of the liquidity loss of all banks affected by the initial shock.

B- **During the feedback round,** the effects of the distress feedback loops within the system are estimated. The change in liquidity positions of individual banks leads to a change in their liquidity risk profiles. In other words, it leads to a change in each bank's liquidity coverage ratio as estimated by Equation 4.2 and the relative liquidity coverage matrix as estimated by Equation 4.3. As the liquidity risk of each bank changes, so does its ability to repay its obligations to its counterparties. This ability is translated into the relative distress matrix as estimated by Equation 4.4. The market values of the interbank assets are re-estimated based on the expected value to be collected from counterparties. We estimate this expected value using a distress propagation factor that is directly derived from the relative distress matrix as follows:

$$A^B_{ij}(t) = max\left[0\ ,\quad A^B_{ij}(0)\Big(\frac{d_{ij}(0)}{d_{ij}(t)}\Big)\right] \tag{4.15}$$

where $A^B_{ij}(t)$ and $A^B_{ij}(0)$ are the interbank assets of bank i with bank j at time steps t and 0 of the distress propagation process, respectively; whereas $d_{ij}(t)$ and $d_{ij}(0)$ are the distress of bank i relative to bank j at time steps t and 0 of the distress propagation process, respectively. The idea is that, when the distress of bank j increases, bank i's exposure to bank j deteriorates proportionally, and if bank j becomes insolvent, bank i loses its assets with bank j. In fact, Equation 4.15 assumes a zero recovery rate, an assumption that is widely followed in the financial contagion literature (see Gai and Kapadia, 2010; Markose, Giansante and Shaghaghi, 2012). The mark to market process is represented by the dashed lines in Figure 4.3. The change in the interbank assets matrix leads to repeating the same sequence of distress propagation in the system. This process continues until the initial shock to the system decays when no further significant changes in the system are expected.

After the second round of distress propagation concludes, the system arrives at a new steady state. We then estimate a few metrics to examine the stability of this system which we outline in Section 4.5.4.

4.5.3 Default Propagation Process

The stress test framework that we provide is capable of bridging the space between illiquidity and insolvency. This is possible due to the fact that we model the evolution of insolvency in terms of illiquidity as explained in detail in Section 4.4 and outlined by the far left column in Figure 4.3. Under each distress scenario, as the liquidity risk of each bank evolves, so does its default risk. With every step in the unfolding of the distress scenario, the solvency status of each bank changes in parallel with the changes in its liquidity status. We monitor these changes by estimating for each bank the absolute change in equity, the distance to insolvency (see Equation 4.11) and the probability of default (see Equation 4.12).

4.5.4 Stress Test Output

The stress test framework presented here provides a variety of output metrics that aim to depict the individual banks and the system's stability. These metrics are presented in the bottom row in Figure 4.3. We briefly explain these metrics below.

A- **DistressRank**

DistressRank provides a convenient way to depict the systemic vulnerability of each bank in the system. It is estimated based on the relative distress matrix and thus reflects the relative vulnerability of each bank to the distress of its counterparties. Banks with higher DistressRank measure are more vulnerable to system-wide shocks than otherwise comparable banks. The exact method of estimating DistressRank is explained in more detail in Section 4.3.4.

B- **Distress Dependence Matrix**

The distress dependence matrix provides a more detailed method to examine the systemic vulnerability of each bank in the system. In particular, for each pair of banks in the system, we estimate the pairwise conditional probability of illiquidity. The matrix is row-wise meaning that it shows the probability of illiquidity of the bank specified in the row, given that the bank specified in the column has become illiquid. Thus, it provides an indicator of distress contagion possibilities within the system.

C- **Default Dependence Matrix**

The default dependence matrix is another way to depict the dependency within the system in detail and at the same time linking illiquidity to insolvency. In particular, for each pair of banks in the system, we estimate the probability of insolvency of a given bank conditional on the other bank becoming illiquid. The matrix is also row-wise as it provides the probability of insolvency of the bank specified in the row, given that the bank specified in the column has become illiquid. Thus, it provides an indicator of default contagion possibilities within the system.

D- **Systemic Risk Matrix**

The previous metrics provide a convenient way to depict the systemic vulnerability and dependencies within the system. This is very important to assess the contagion possibilities in the system. The stress test also provides another way to do this through a systemic risk matrix which lends itself more to economic interpretation. In this matrix we quantify systemic vulnerability and impact in terms of expected economic loss. We explain the constituents of the systemic risk matrix in detail here as it was not introduced elsewhere.

Similar to previous matrices, each row represents the vulnerability of the bank in this row to the distress of other banks. Let V_{ij} be the expected loss of the bank in row i due to the distress of the bank in column j. This amount of expected loss can be estimated in terms of percentage liquidity loss as:

$$V_{ij} = min\left[1 \quad , \quad \frac{\ell_i(0) - \ell_i(T)}{\ell_i(0)}\right] \tag{4.16}$$

where $\ell_i(T)$ is the amount of liquidity remaining for i at time T after j has become distressed. In dollar terms, the expected loss of bank i relative to bank j is $V_{ij} = \ell_i(0) - \ell_i(T)$. Following the same logic, we can estimate the systemic expected loss of bank i as:

$$V_i = \sum_j \chi_j^L(0) \;\; V_{ij} \tag{4.17}$$

where $\chi_j^L(0)$ is the probability of illiquidity of bank j at $t = 0$. This measure of systemic expected loss represents the systemic vulnerability of bank i measured as the probability-weighted expected loss of bank i due to the distress of any one of the other banks in the system.

Similarly, Let I_{ij} be the relative impact of bank i on bank j which represents the expected loss that the distress of bank i can induce in bank j. We can estimate this amount as:

$$I_{ij} = \frac{\ell_j(0) - \ell_j(T)}{\ell_j(0)} = V_{ji} \tag{4.18}$$

in dollar terms this amount would be $I_{ij} = \ell_j(0) - \ell_j(T) = V_{ji}$. Needless to say is that this measure is exactly equal to the relative vulnerability of bank j relative to bank i. We also estimate a measure for the systemic impact of bank j as the total expected loss induced in all other banks due to the distress of bank j, which is simply the weighted sum of column j in the systemic risk matrix, and is estimated as:

$$I_i = \sum_j \frac{\ell_j(0)}{\sum_j \ell_j(0)} \;\; I_{ij} \tag{4.19}$$

Finally, we provide a measure of the global system-wide expected loss as:

$$\Phi = \sum_i \chi_i^L(0) \;\; I_i \tag{4.20}$$

where Φ is estimated as the probability-weighted average systemic expected loss. This measure can also be used as an indicator of the system-wide stability. The higher the systemic expected loss, the lower the system stability.

4.6 Empirical Application

In this section, we provide an overview of the data used and the main results of applying the stress test framework outlined in Section 4.5 to the U.S. banking system.

4.6.1 Data and Interbank Network Construction

The data used to implement the stress test is related to the largest 25 holding companies in the U.S.[2] For each holding company (bank henceforth), we obtain data about balance sheet holdings, liquidity coverage ratios, and derivatives exposures. The balance sheet data is collected from the Consolidated Financial Statements of banks (FR Y-9C reports) provided by the National Information Centre.[3] From these reports we extract information about total assets, total liabilities, derivatives assets and liabilities, and equity. We use the Quarterly Report on Bank Derivatives Activities from the Office of the Comptroller of the Currency to obtain data about the interbank exposures of each bank.[4] The data about liquidity coverage ratio is hand collected from the annual and quarterly reports of each bank. From these reports we collect the reported amounts of high quality liquid assets, net cash outflows expected over the next 30 days, and the liquidity coverage ratio of each bank. The data used to perform the stress test is

[2]We use the term holding companies to refer to all types of holding companies under the direct supervision of the Federal Reserve Board including domestic bank holding companies (BHC), savings and loan holding companies (SLHC), U.S intermediate holding companies (IHC) and securities holding companies (SHC)

[3]Data is obtained from the website of Federal Financial Institutions Examination Council (FFIEC) and is available at https://www.ffiec.gov/nicpubweb/nicweb/nichome.aspx

[4]Data is obtained from the Office of the Comptroller of the Currency (OCC) and is available at https://www.occ.gov/topics/capital-markets/financial-markets/derivatives/derivatives-quarterly-report.html

as of June 30, 2017. This is the most recently available and complete set of data that includes disclosures about the liquidity coverage ratio of the large U.S. banks.

We use the interbank derivatives exposures as they represent liquidity flows between banks and are included in calculating the liquidity coverage ratio that banks disclose in their reports (Basel Committee on Banking Supervision, 2013*b*). Any change in the amounts of derivatives assets or liabilities leads to changes in the estimated liquidity coverage ratio, and hence can be used as a way to monitor distress propagation within the interbank market. The network of derivatives assets and liabilities within the interbank market can be represented by the following matrix:

$$A^B = \begin{bmatrix} A_{11} & \dots & A_{1j} & \dots & A_{1N} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ A_{i1} & \dots & A_{ij} & \dots & A_{iN} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ A_{N1} & \dots & A_{Nj} & \dots & A_{NN} \end{bmatrix}$$

where A_{ij} represents the derivatives assets of bank i with bank j or the derivatives liabilities of bank j to bank i. The matrix size is $N \times N$ where N is the number of banks. The sum of a row represents the derivatives assets of the respective bank where $A_i^B = \sum_j A_{ij}$ and the sum of a column represents the derivatives liabilities of the respective bank where $L_j^B = \sum_i A_{ij}$. Unfortunately, the network of interbank derivatives exposures is not observable, as banks do not provide granular data about their bilateral exposures.

Since information on the the bilateral interbank exposures is essential for our analysis, we estimate this data to fill in the interbank matrix. To this end, we use the Minimum Density (MD) method suggested by Anand, Craig and Von Peter (2015). The idea behind MD is to distribute each bank's assets and liabilities among the lowest possible number of counterparties. The economic rational for this is that the interbank network appears to be constructed based on relationships and as a result is sparse (Cocco, Gomes and Martins, 2009) as banks aim to minimise the costs of establishing and maintaining linkages including the costs of information processing, and risk management. This rationale is supported by studies of real world financial networks of the United States (Bech and Atalay, 2010) and Germany (Craig and von Peter, 2014).

4.6.2 Results of the Stress Test

The proposed stress test provides a variety of metrics to assess the system resilience. We provide here an overview of the system before applying any stress scenarios. Then, we provide the results of applying the first and second stress scenarios to assess the system stability and systemic interdependencies, respectively.

4.6.2.1 System Profile

As discussed in Section 4.3, DistressRank provides a relative rank of all banks within a system with regard to their vulnerability to the distress of other banks. In addition, DistressRank can be estimated before applying any stress scenarios which provides the advantage of depicting the stability of the system at any point of time. We use this indicator to provide an overview of the current state of the U.S. banking system, as of 30 June 2017. Figure 4.4 shows the interbank market network which comprises the 25 individual banks included in our stress test. On this network, the size of each bank is scaled proportionally to its DistressRank. As illustrated, JPMorgan Chase is the most vulnerable bank, followed by Goldman Sacks. While the two least vulnerable banks are HSBC North America Holdings and PNC Financial Services Group. The other banks have comparable ranks. The same result can be seen from Figure 4.5, which shows the exact values of the DistressRank indicator for each bank.

There is a striking observation that can be noticed from Figure 4.4 about banks' DistressRank. The asset size of a bank does not entail its systemic vulnerability. For example, Bank of America is the second largest bank measured by total assets, however, its DistressRank is comparable to other smaller banks such as US Bank Corporation and Citizens Financial Group. Moreover, even a bank's interbank assets or liabilities alone do not completely determine its DistressRank. An example of this is Citi Group which has the largest interbank assets but rank third based on DistressRank. In fact, DistressRank is affected by the interconnectedness within the interbank market in addition to the size of both interbank assets and liabilities. This finding has some important implications for the methodology of identifying global systemically important banks (G-SIBs) (Basel Committee on Banking Supervision, 2013*a*). In particular, the methodology should consider systemic distress as well as systemic importance in measuring a bank's interconnectedness as one of the indicators used to identify G-SIBs.

4.6.2.2 System Stability

We turn now to assessing the stability of the banking system following our proposed stress testing framework. To this end, we implement the first stress scenario (as explained in Section 4.5) in which a uniform shock is applied to all banks in order to assess the resilience of the banking system to macroeconomic shocks. We use a vector of shocks that ranges from 1% to 25%, which are extreme enough, yet plausible. We can think of a shock as resembling a severe change in risk free rates or widening in credit spreads that affect all banks simultaneously. The initial shock leads to a proportional reduction in the interbank assets of all banks leading to reductions in their liquidity positions. Then, the distress propagation process unfolds. The stress testing exercise provides a variety of output metrics

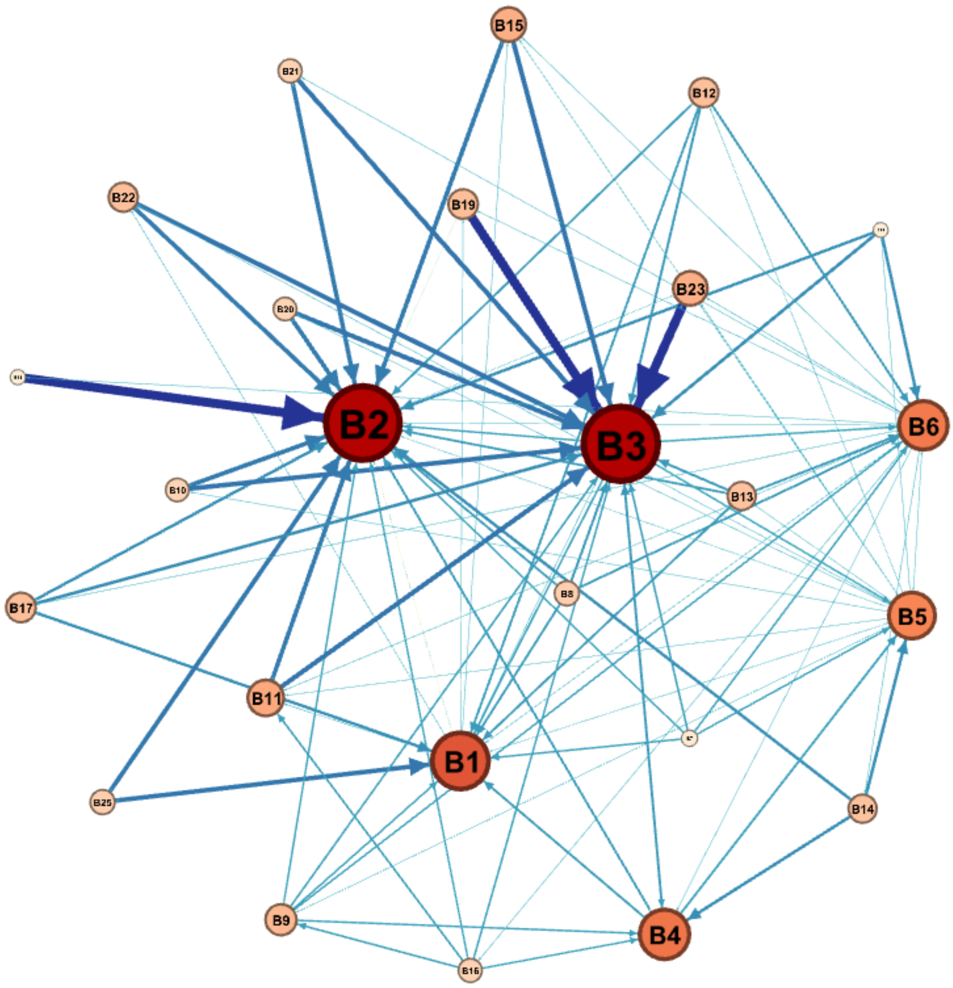


FIGURE 4.4: The distress network and DistressRank of individual banks in the system. Nodes represent banks and links represent interbank exposures. The size and color of each node are scaled proportionally to the value of its DistressRank. The width and color of each link are scaled proportionally to the value of relative distress induced from the bank at the start of the link to the bank at the end of the link. Number of banks is 25. Banks' names are coded from B1 to B25 where B1: Citi Group, B2: Goldman Sachs Group, B3: JPMorgan Chase, B4: Bank of America, B5: Morgan Stanley, B6: Wells Fargo, B7: HSBC North America, B8: Mizuho America, B9: State Street, B10: RBC USA, B11: Credit Suisse USA, B12: Bank of NY Mellon, B13: Barclays US, B14: PNC Group, B15: US Bancorp, B16: Northern Trust, B17: SunTrust Bank, B18: TD Group US, B19: DB USA, B20: Capital One, B21: MUFG Americas, B22: KeyCorp, B23: Citizens Financial Group, B24: BB&T Corp, B25: Regions Financial Group.

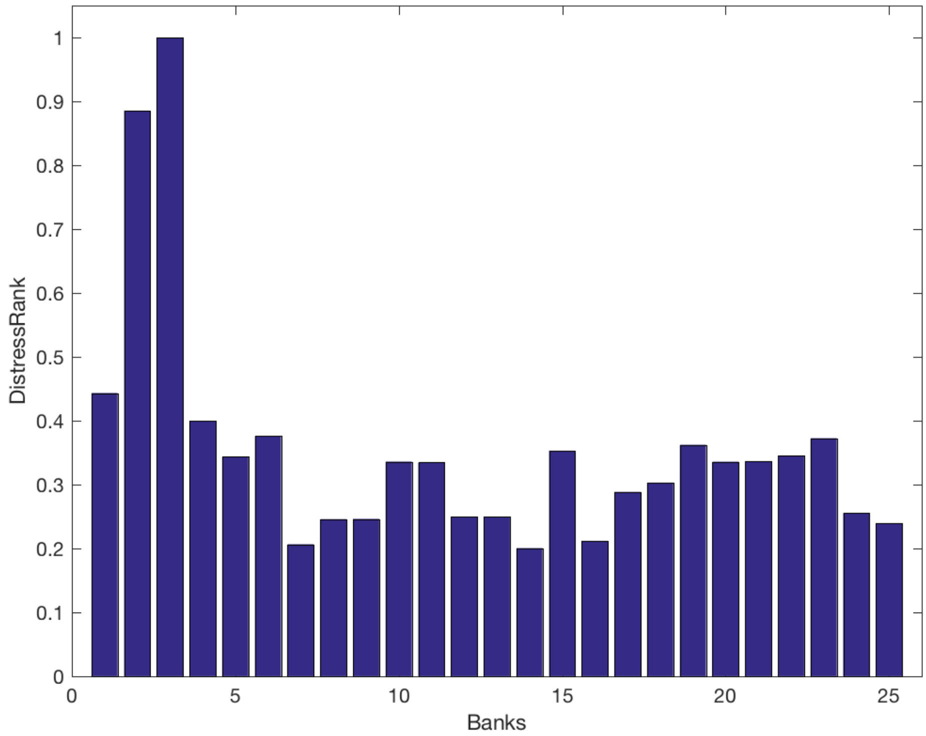


FIGURE 4.5: The DistressRank of individual banks in the system. Number of banks is 25. Banks' names are coded from 1 to 25 where 1: Citi Group, 2: Goldman Sachs Group, 3: JPMorgan Chase, 4: Bank of America, 5: Morgan Stanley, 6: Wells Fargo, 7: HSBC North America, 8: Mizuho America, 9: State Street, 10: RBC USA, 11: Credit Suisse USA, 12: Bank of NY Mellon, 13: Barclays US, 14: PNC Group, 15: US Bancorp, 16: Northern Trust, 17: SunTrust Bank, 18: TD Group US, 19: DB USA, 20: Capital One, 21: MUFG Americas, 22: KeyCorp, 23: Citizens Financial Group, 24: BB&T Corp, 25: Regions Financial Group.

which we outline below.

Figure 4.6 shows the number of distressed banks that become illiquid or insolvent following each shock. As would be expected, both numbers increase with the increase in the shock applied to the system. It is worth noting that the increase in both numbers is not linear. This is due to the fact that whether a distressed bank becomes illiquid or insolvent depends not only on its liquidity position but also the liquidity position of its counterparties and the severity of the shock. As illustrated, banks are resilient to small shocks up to 4%, while they reach the illiquidity point starting from shocks of as low as 5%. The insolvency point is

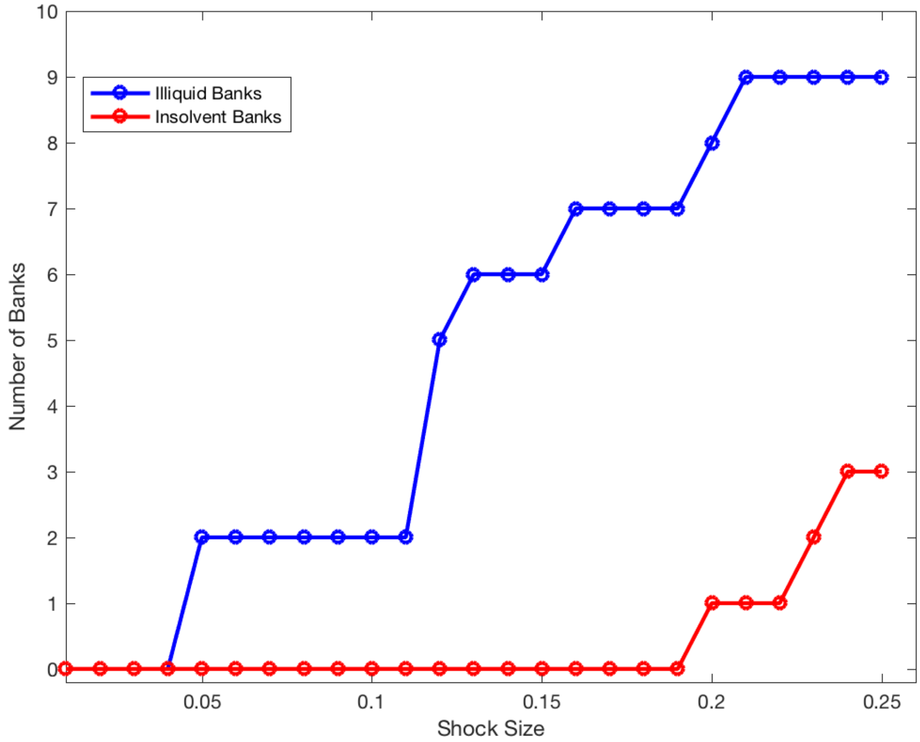


FIGURE 4.6: Number of Illiquid and Insolvent Banks due to a specific shock to the interbank assets. Shock size ranges from 1% to 25% of interbank assets.

reached much later as the first time a bank becomes insolvent occurs at a shock level of 20%.

Figure 4.7 provides a decomposition of systemic loss into first round loss due to the initial shock and feedback loss occurring during second and upper rounds. Systemic loss is estimated at the system level as the total reduction in the value of banks' liquid assets. A striking observation that is shown in this figure is that the feedback loss can be as large as the initial loss due to the systemic shock. It can also exceed the initial loss at high levels of shocks. This observation highlights the need to consider the feedback loss due to interconnectedness between banks while designing macroprudential stress tests.

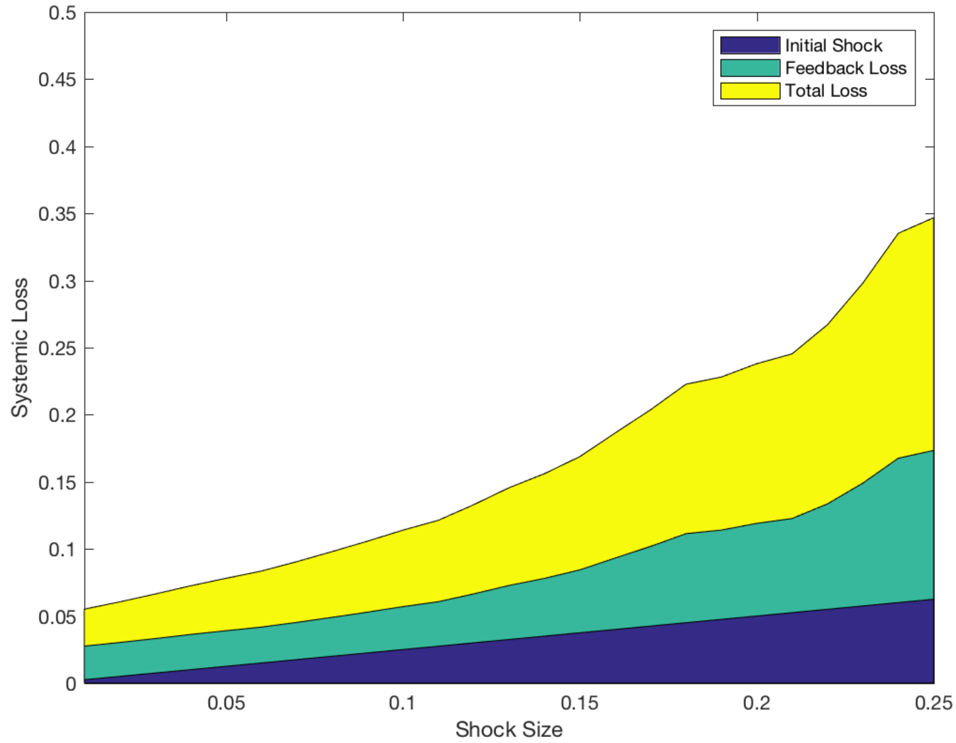


FIGURE 4.7: Decomposition of systemic loss into first round loss due to the initial shock and feedback loss occurring during second and upper rounds. Shock size ranges from 1% to 25% of interbank assets. Systemic loss is estimated at the system level as the total reduction in the value of banks' assets.

Another way to highlight the role of interconnectedness is to consider the relationship between DistressRank and systemic feedback loss at the bank level. We use DistressRank as a measure of systemic distress that captures interconnectedness, while a bank's systemic feedback loss is estimated as its share in the total feedback loss at the system level due to a specific shock. We limit the analysis here to a shock size of 10%. The result of this exercise is shown in Figure 4.8. As illustrated, there seems to be a positive relationship between the DistressRank of a bank and its systemic feedback loss. To investigate this further, we run a simple regression of systemic feedback loss on DistressRank. The results show a positive slope that is significant at a 95% significance level with adjusted R^2 of 61%. This result confirms the importance of considering interconnectedness in designing macroprudential stress tests.

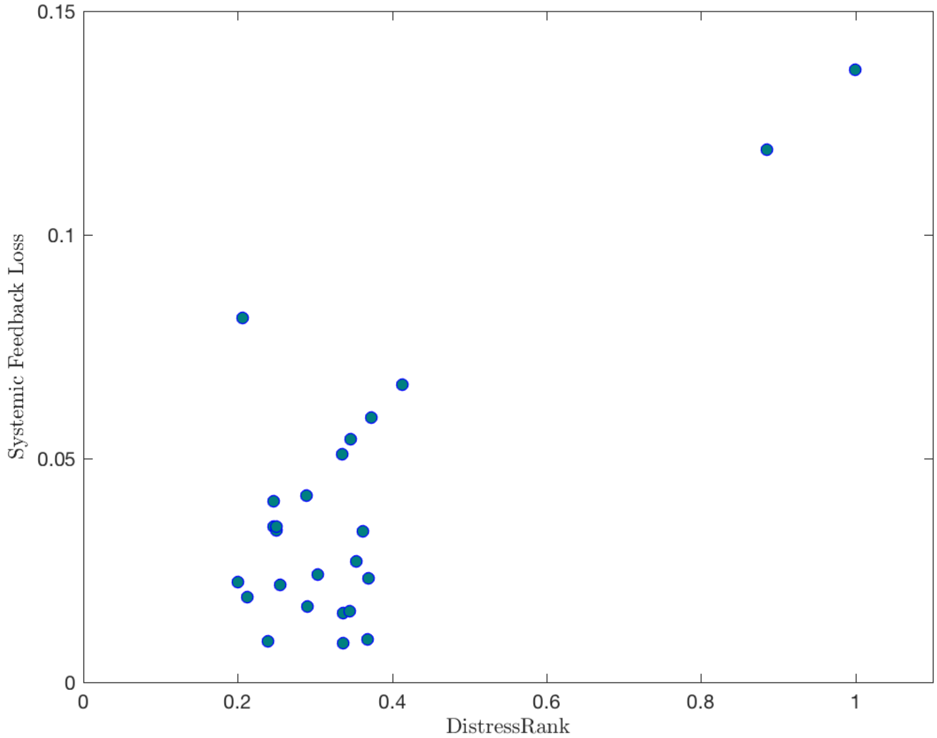


FIGURE 4.8: DistressRank and Systemic Feedback Loss. A bank's systemic feedback loss is estimated as its share in the total feedback loss at the system level due to a specific shock. Shock size is 10% of interbank assets. Each circle in the figure represents a bank.

Finally, we can illustrate the resilience of the system to shocks by tracing the change in the probability of illiquidity and the probability of insolvency of each bank following a specific shock. Figure 4.9 and Figure 4.10 show, for each bank, the change in probability of illiquidity and the change in probability of insolvency, respectively. Again, we limit the analysis to a shock size of 10% of interbank assets. As can be seen clearly from these figures, both probabilities show remarkable increases with almost all banks having higher probabilities of illiquidity and insolvency following the shock. While some banks become illiquid following the shock, some of them have their probability of insolvency nearly doubled following the shock.

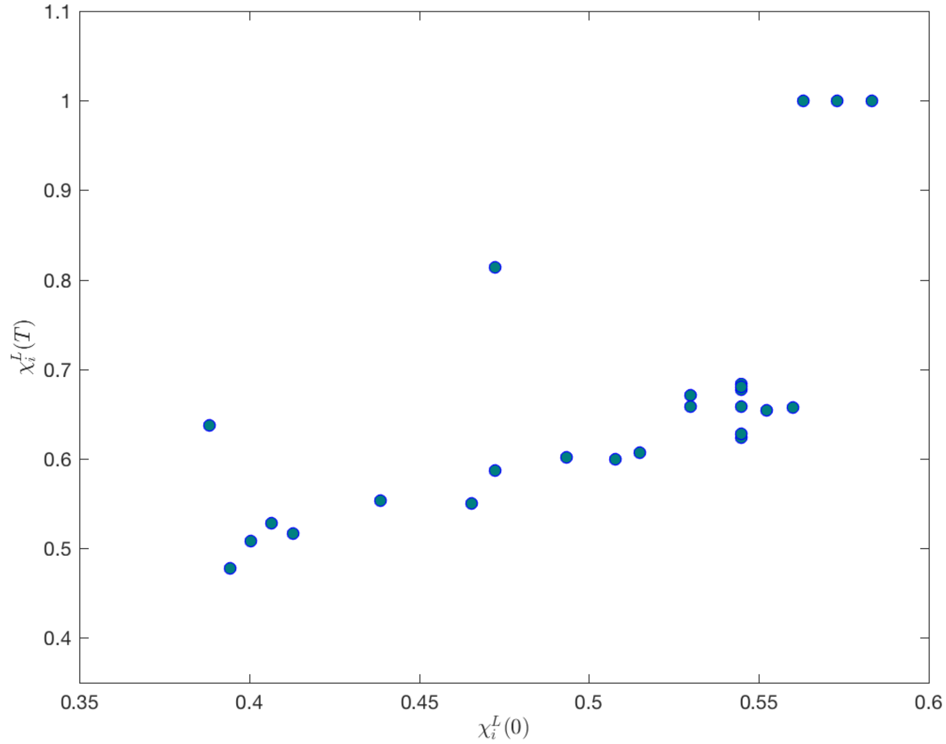


FIGURE 4.9: Change in Probability of Illiquidity for each bank in the system due to a specific shock. Shock size is 10% of interbank assets. $\chi_i^L(0)$ and $\chi_i^L(T)$ are the probability of illiquidity of bank i before and after applying the shock to the system, respectively. Each circle in the figure represents a bank.

4.6.2.3 Systemic Interdependencies

So far, our analysis of stability has focused on the resilience of the system to a system wide shock that represents a macroeconomic shock. We extend the analysis here to examine the interdependencies within the system. To this end, we implement the second stress scenario which involves shocking banks sequentially (see Section 4.5 for more details). The results of this exercise are shown below.

A- Systemic Distress Dependence

The distress dependence matrix provides insight into the interlinkages between banks and how vulnerable they are to the distress of each other. In particular, the output shown by this matrix can be viewed as the conditional probability of

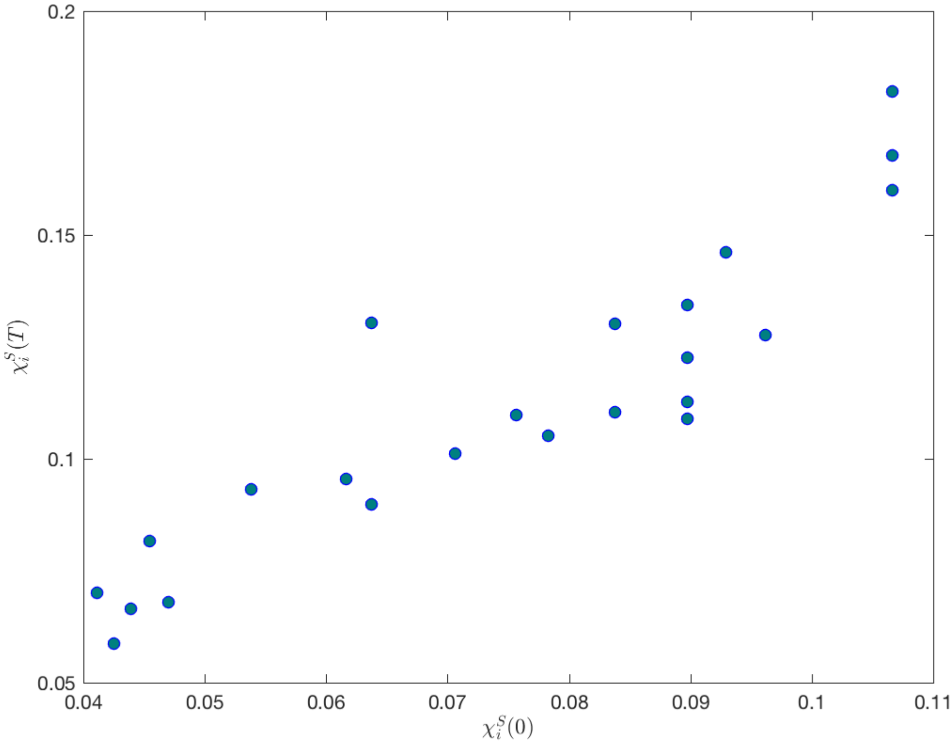


FIGURE 4.10: Change in Probability of Insolvency for each bank in the system due to a specific shock. Shock size is 10% of interbank assets. $\chi_i^S(0)$ and $\chi_i^S(T)$ are the probability of insolvency of bank i before and after applying the shock to the system, respectively. Each circle in the figure represents a bank.

illiquidity of the bank in the row relative to the bank in the column. In Figure 4.11, we present the distress dependence matrix estimated for the group of 25 U.S. banks included in the stress test. In this matrix, each cell represents the change in the probability of illiquidity of the bank in the row given that the bank in the column has become illiquid. For better illustration, we provide the matrix as a heatmap.

As can be seen from the matrix, distress dependence is higher among banks that are located at the upper left quadrant of the matrix. Put differently, large changes in the probability of illiquidity are associated with banks that have large interbank exposures with each other. For example, Citi Group is more vulnerable to the distress of Goldman Sachs, JP Morgan and Bank of America compared

Bank	CITI	GS	JPM	BOA	MS	WF	HSBC	MIZ	SS	RBC	CRS	BNM	BAR	PNC	USP	NTR	SUN	TD	DB	CAP	MUFG	KEY	CIT	BBT	REG	
CITIGROUP	1.06	0.15	0.34	0.56	0.05	0.04	0.01	0.00	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	CITI
GOLDMAN SACHS	0.87	0.75	0.21	0.32	0.67	0.09	0.04	0.00	0.05	0.01	0.00	0.10	0.00	0.05	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	GS
JPMORGAN CHASE	0.18	0.18	0.57	0.07	0.13	0.08	0.01	0.00	0.05	0.00	0.02	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	JPM
BANK OF AMERICA	0.07	0.07	0.52	0.67	0.05	0.04	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	BOA
MORGAN STANLEY	0.84	0.33	0.14	0.17	1.24	0.06	0.13	0.00	0.01	0.00	0.00	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	MS
WELLS FARGO	0.06	0.10	0.03	0.02	0.04	0.20	0.00	0.00	0.01	0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	WF
HSBC N AMERICA	0.22	0.02	0.03	0.04	0.01	0.01	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	HSBC
MIZUHO	0.44	0.03	0.07	0.09	0.01	0.01	0.00	0.23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	MIZ
STATE STREET	0.10	0.30	0.04	0.05	0.06	0.01	0.01	0.00	0.59	0.00	0.00	0.02	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	SS
RBC USA HOLDCO	0.01	0.01	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	RBC
CREDIT SUISSE	0.06	0.04	0.01	0.02	0.03	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	CRS
BANK OF NY MELLON	0.03	0.07	0.01	0.02	0.07	0.01	0.01	0.00	0.00	0.00	0.00	0.16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	BNM
BARCLAYS	0.02	0.04	0.01	0.01	0.04	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	BAR
PNC FNCL SVC	0.02	0.05	0.01	0.01	0.03	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	PNC
U S BC	0.05	0.01	0.01	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	USP
NORTHERN TR	0.04	0.18	0.02	0.03	0.04	0.01	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	NTR
SUNTRUST	0.03	0.02	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	SUN
TD GRP US	0.03	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	TD
DB USA	0.09	0.07	0.02	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.00	0.00	0.00	0.00	0.00	0.00	DB
CAPITAL ONE	0.01	0.02	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	CAP
MUFG AMERS	0.02	0.11	0.01	0.02	0.02	0.03	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.00	0.00	0.00	0.00	MUFG
KEYCORP	0.05	0.06	0.01	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.00	0.00	0.00	KEY
CITIZENS FNCL	0.05	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	CIT
BB&T	0.01	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	BBT
REGIONS	0.01	0.03	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	REG

FIGURE 4.11: Distress Dependence Matrix. Each cell in the matrix represents the change in the probability of illiquidity of the bank in the row given that the bank in the column has become illiquid. Bank names are as in Figure 4.4. The matrix is presented as a heatmap where cells colors are scaled from green for low values to red for high values.

to other banks in the sample. Another interesting observation is that, the four most vulnerable banks, namely Goldman Sachs, Morgan Stanley, Citi Group and Bank of America, stem their vulnerability from each other. This is explained by the fact that the exposure of these banks to each other represent a large portion of their overall interbank assets. Any distress that arises with one of them will definitely lead to a serious liquidity problem with the others. It is also worth noting that banks in the lower right quadrant seem to be resilient to the distress of each other mainly due to the fact that they have limited exposures to each other.

B- Systemic Default Dependence

The stress test output includes another interesting matrix called the default dependence matrix. This matrix examines the possibility that illiquidity distress evolves to become insolvency default. It is also similar to the distress dependence matrix in that it provides insight into the possibility of contagion within the system. The default dependence matrix is illustrated in Figure 4.12 where each row represents the change in the probability of insolvency of the bank in the row given that the bank in the column has become illiquid. Again, each cell can be viewed as the conditional probability of insolvency of the bank in the row relative to the bank in the column. For better illustration, the matrix is shown as a heatmap.

The same observations on the distress dependence matrix apply also here. The default dependence seems to be higher among banks in the upper left quadrant and lower among banks in the lower right quadrant. Again, this is due to concentration of exposure between big banks and each other or big banks and other smaller banks, while exposures between smaller banks and each other are limited. For example, Goldman Sachs appears to be the most vulnerable bank to shocks from its counterparties and specially from Citi Group and Morgan Stanley.

If Citi Group becomes illiquid, the probability of insolvency of Goldman Sachs increase by a factor of 3.78 times. Any distress that arises with Citi Group will definitely lead to a serious liquidity problem with any one of its counterparties.

C- Systemic Risk Matrix

The systemic risk matrix provides an estimation of systemic expected loss of each bank due to other banks distress. It provides another way to study the interdependencies among banks by quantifying the systemic expected economic loss due to systemic distress between pairs of banks. Each cell in the matrix represents the expected loss of the bank in the row given that the bank in the column has become illiquid. The matrix is shown in Figure 4.13. For better illustration, we provide the matrix as a heatmap.

The systemic risk matrix confirms the same results obtained by analysing distress and default dependence matrices. As would be expected, systemic loss is more concentrated in the upper left quadrant and limited among banks in the lower right quadrant. Counterparties of large banks are more vulnerable to systemic risk compared to others. If Citi Group becomes illiquid, it induces a 17.3% system wide expected loss. Goldman Sachs is the most vulnerable bank with an expected loss of nearly 58%. The expected systemic loss is 30% which represents a system wide stability measure. The higher this indicator is the more fragile the system is, representing more interconnectedness and/or higher probabilities of distress.

Another interesting finding from the systemic risk matrix is related to the relationship between systemic impact (SysImpact row) and systemic vulnerability (SysVul column) of each bank. We illustrate this relationship in Figure 4.14.

Bank	CITI	GS	JPM	BOA	MS	WF	HSBC	MIZ	SS	RBC	CRS	BNM	BAR	PNC	USP	NTR	SUN	TD	DB	CAP	MUFG	KEY	CIT	BBT	REG	
CITIGROUP	3.91	0.37	0.96	1.91	0.13	0.10	0.01	0.00	0.03	0.00	0.01	0.02	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	CITI
GOLDMAN SACHS	3.78	2.90	0.54	0.87	2.46	0.21	0.10	0.00	0.12	0.02	0.01	0.23	0.01	0.12	0.02	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.01	GS
JPMORGAN CHASE	0.48	0.50	2.28	0.18	0.35	0.20	0.03	0.01	0.13	0.00	0.04	0.03	0.00	0.01	0.02	0.01	0.00	0.00	0.02	0.01	0.01	0.01	0.00	0.01	0.00	JPM
BANK OF AMERICA	0.17	0.15	1.73	2.50	0.11	0.08	0.01	0.00	0.05	0.00	0.01	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	BOA
MORGAN STANLEY	3.59	0.92	0.33	0.44	4.05	0.13	0.31	0.00	0.03	0.00	0.00	0.04	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	MS
WELLS FARGO	0.14	0.25	0.07	0.05	0.08	0.53	0.01	0.00	0.02	0.00	0.00	0.04	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	WF
HSBC N AMERICA	0.73	0.04	0.09	0.12	0.02	0.01	0.88	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	HSBC
MIZUHO	1.99	0.09	0.20	0.25	0.04	0.03	0.00	0.78	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	MIZ
STATE STREET	0.26	0.98	0.09	0.13	0.16	0.04	0.02	0.00	2.74	0.00	0.00	0.04	0.00	0.02	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	SS
RBC USA HOLDCO	0.02	0.02	0.01	0.01	0.08	0.00	0.01	0.00	0.00	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	RBC
CREDIT SUISSE	0.15	0.10	0.03	0.04	0.08	0.01	0.01	0.00	0.00	0.00	0.61	0.01	0.00	0.00	0.00	0.18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	CRS
BANK OF NY MELLON	0.07	0.18	0.03	0.04	0.18	0.01	0.01	0.00	0.01	0.00	0.00	0.42	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	BNM
BARCLAYS	0.04	0.10	0.02	0.02	0.11	0.06	0.01	0.00	0.00	0.00	0.00	0.01	0.32	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	BAR
PNC FNCL SVC	0.04	0.14	0.02	0.02	0.07	0.05	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	PNC
U S BC	0.14	0.02	0.02	0.03	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	USP
NORTHERN TR	0.10	0.53	0.05	0.07	0.10	0.02	0.01	0.00	0.01	0.00	0.00	0.02	0.00	0.01	0.00	0.81	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	NTR
SUNTRUST	0.09	0.04	0.02	0.02	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	SUN
TD GRP US	0.05	0.01	0.02	0.02	0.02	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.38	0.00	0.00	0.00	0.00	0.00	0.00	0.00	TD
DB USA	0.21	0.16	0.04	0.05	0.04	0.01	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.34	0.00	0.00	0.00	0.00	0.00	0.00	DB
CAPITAL ONE	0.01	0.06	0.01	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.00	0.00	0.00	0.00	0.00	CAP
MUFG AMERS	0.06	0.27	0.03	0.04	0.06	0.08	0.01	0.00	0.01	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.26	0.00	0.00	0.00	0.00	MUFG
KEYCORP	0.12	0.16	0.03	0.04	0.06	0.01	0.01	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.15	0.00	0.00	0.00	KEY
CITIZENS FNCL	0.13	0.01	0.02	0.03	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.00	0.00	CIT
BB&T	0.01	0.01	0.00	0.01	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.09	0.00	BBT
REGIONS	0.02	0.09	0.01	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.08	REG

FIGURE 4.12: Default Dependence Matrix. Each cell in the matrix represents the change in the probability of insolvency of the bank in the row given that the bank in the column has become illiquid. Bank names are as in Figure 4.4. The matrix is presented as a heatmap where cells colors are scaled from green for low values to red for high values.

Bank	CITI	GS	JPM	BOA	MS	WF	HSBC	MIZ	SS	RBC	CRS	BNM	BAR	PNC	USP	NTR	SUN	TD	DB	CAP	MUFG	KEY	CIT	BBT	REG	SysVul	
CITIGROUP	0.46	0.07	0.16	0.25	0.03	0.02	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.43	CITI
GOLDMAN SACHS	0.36	0.31	0.10	0.14	0.28	0.04	0.02	0.00	0.03	0.00	0.00	0.05	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.58	GS
JPMORGAN CHASE	0.10	0.10	0.30	0.04	0.08	0.05	0.01	0.00	0.03	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.33	JPM
BANK OF AMERICA	0.04	0.03	0.23	0.29	0.02	0.02	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.29	BOA
MORGAN STANLEY	0.35	0.15	0.07	0.08	0.52	0.03	0.06	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.53	MS
WELLS FARGO	0.03	0.05	0.02	0.01	0.02	0.10	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.11	WF
HSBC N AMERICA	0.16	0.01	0.03	0.03	0.00	0.00	0.18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.21	HSBC
MIZUHO	0.32	0.03	0.05	0.06	0.01	0.01	0.00	0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.30	MIZ
STATE STREET	0.06	0.18	0.02	0.03	0.04	0.01	0.00	0.00	0.35	0.00	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.34	SS
RBC USA HOLDCO	0.01	0.01	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	RBC
CREDIT SUISSE	0.04	0.03	0.01	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.13	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.14	CRS
BANK OF NY MELLON	0.02	0.04	0.01	0.01	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.09	BNM
BARCLAYS	0.01	0.03	0.00	0.01	0.03	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.08	BAR
PNC FNCL SVC	0.01	0.04	0.00	0.01	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	PNC
U S BC	0.04	0.00	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	USP
NORTHERN TR	0.03	0.12	0.01	0.02	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.18	NTR
SUNTRUST	0.02	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	SUN
TD GRP US	0.02	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	TD
DB USA	0.05	0.04	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.08	DB
CAPITAL ONE	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.02	CAP
MUFG AMERS	0.01	0.06	0.01	0.01	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.08	MUFG
KEYCORP	0.03	0.04	0.01	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.07	KEY
CITIZENS FNCL	0.04	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.04	CIT
BB&T	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.02	BBT
REGIONS	0.01	0.02	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.03	REG
SysImpact	0.173	0.089	0.136	0.129	0.093	0.038	0.010	0.001	0.016	0.001	0.003	0.013	0.002	0.005	0.002	0.002	0.000	0.002	0.002	0.001	0.001	0.001	0.000	0.001	0.001	0.30	

FIGURE 4.13: Systemic Risk Matrix. Each cell in the matrix represents the expected loss of the bank in the row given that the bank in the column has become illiquid. Bank names are as in Figure 4.4. The matrix is presented as a heatmap where cells colors are scaled from green for low values to red for high values. SysImpact stands for Systemic Impact of the bank in the column and is estimated as in Equation 4.19. SysVul stands for Systemic Vulnerability of the bank in the row and is estimated as in Equation 4.17. The cell in the intersection of SysImpact and SysVul represents the Systemic Loss which is estimated as in Equation 4.20.

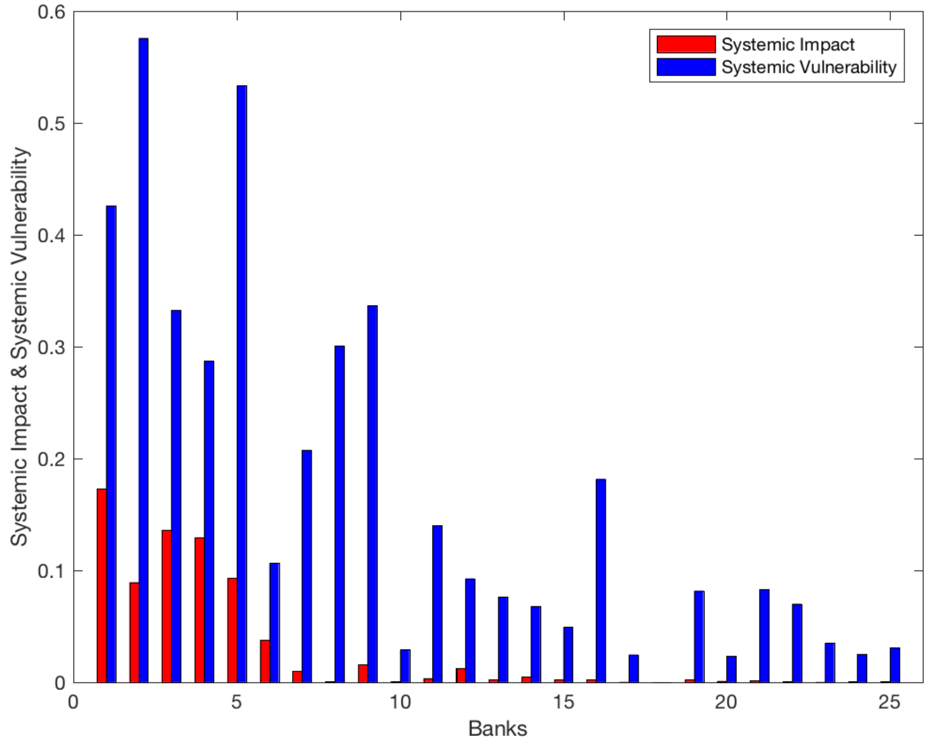


FIGURE 4.14: The Systemic Impact and Systemic Vulnerability of banks. Systemic Impact of individual banks is estimated as in Equation 4.19. Systemic Vulnerability of individual banks is estimated as in Equation 4.17.

While most banks seem to be vulnerable to shocks from other banks as measured by their expected loss, not all banks have significant systemic impact as the systemic impact values of smaller banks seem to be negligible. Only big banks have systemic impact levels that are significant enough to be comparable to their systemic vulnerability. In addition, banks do not have the same ranking based on systemic impact and systemic vulnerability indicators. This finding has important implications for designing a macroprudential stress test that aims to consider interconnectedness. In particular, using measures of systemic impact is not sufficient to reveal the vulnerabilities within a system. A comprehensive analysis of interconnectedness should consider systemic vulnerability as well as systemic impact of the financial institutions in the system.

4.7 Conclusion

This chapter proposes a macroprudential stress testing approach and illustrates its empirical application on a data set of the U.S. banking system. The innovative features of the proposed macroprudential stress test were inspired by the recent regulatory recommendations to strengthen the systemic focus and to more deeply consider the interactions between liquidity and solvency risks in designing effective macroprudential stress tests.

The proposed approach provides a tool for the banking system supervisors to analyse the current state of the system stability. The empirical application of the stress test shows how it can be effectively used to identify the systemic vulnerability of individual banks as well as the resilience of the system as a whole to economic risks. The findings confirm the need to consider interconnectedness in designing macroprudential stress tests. At the bank level, the results confirm that interlinkages play a significant role in identifying individual banks vulnerability. On this premise, we propose DistressRank as a measure of the systemic distress of a bank. The results show that a bank's DistressRank is associated with its systemic feedback loss. At the system level, the systemic loss due to feedback loops was shown to be significant compared to the direct loss that results from the initial shock to the system. Ignoring these feedback effects may lead to a significant underestimation of systemic loss.

Moreover, the proposed approach provides a tool for the banking system supervisors to monitor the evolution of contagion and systemic risk within the system due to endogenous or exogenous shocks. Applying the stress test framework to the U.S. banking system shows how it can be effective for monitoring and assessing interdependencies among banks. Our findings provide an insight into the possibilities of distress propagation within the system. An important finding that is shown here is that banks that are not directly connected together through interbank assets or liabilities are still subject to distress from each other through common counterparties. These findings can form the basis for intervention by policy makers in case a specific bank has become distressed and there is a need to identify banks that will be affected the most.

In conclusion, the proposed macroprudential stress test is able to reveal the systemic vulnerabilities in a banking system, giving policymakers insight into the system resilience. Although the framework demonstrated here was applied using a reconstructed network of interbank exposures, this data was sufficient to highlight the merit of the proposed stress test framework. The availability of granular bank data would only increase the robustness of the analysis. Extending the analysis to include additional banks would provide a tool for policymakers to more comprehensively monitor and regulate the interdependencies in the banking system and the resilience of the system as a whole. Another avenue for extending the work done here is to consider the reactions of banks to shocks and the possibilities of deleveraging and its impact on the magnitude of systemic loss.

Chapter 5

Conclusions

5.1 Overview

This thesis has studied a number of financial stability problems. Section 5.2 summarises the overall content and the scientific contributions of each of the three main chapters in this thesis. Section 5.3 presents an overview of the limitations of the selected techniques and methodologies. Section 5.4 identifies directions for future research. Finally, a concluding remark is provided in Section 5.5.

5.2 Summary of Contributions and Policy Implications

This thesis has introduced new models to study the dynamics of systemic risk and contagion in securitisation, interbank and derivatives markets. It has analysed different systemic aspects and interactions between liquidity risk, funding risk, and solvency risk. This thesis, in the author's view, has provided different contributions to the field of financial stability and different implications for macroprudential policy.

Chapter 2 has analysed the impact of securitisation activities on bank stability and systemic risk. It has contributed to literature by developing a structural model of bank stability as a function of securitisation, and by proposing a new index (*S-score*) that measures the net impact of securitisation activities on bank stability and the stability of the banking system as a whole. Results on the dynamics of the *S-score* measure at both the individual bank level and the banking system level have shown that securitisation activities have a destabilising effect on securitiser banks. Results have also shown that securitisation tends to increase commonality of asset returns among banks leading to increased interconnectedness and systemic risk. Chapter 2 has also shown that low monetary policy short-term interest rates in the aftermath of the global financial crisis have mitigated the destabilising effect of securitisation on banks. These findings have various policy implications. Given the current increasing pace in monetary policy tightening, these findings are of great interest to policy makers in their attempts to revive securitisation markets. In fact, Chapter 2 provides a framework for regulators to think about the effects of securitisation at the bank level and the banking system level. The results of this chapter highlights the importance that regulators consider the effects of securitisation on a risk-adjusted performance basis, and to consider the different channels through which securitisation affects bank stability.

Chapter 3 has analysed the interaction between margin procyclicality and systemic liquidity risk. This chapter has shown that distress due to margin procyclicality in the OTC derivatives market can spillover to the interbank market leading to episodes of systemic liquidity risk. Interconnectedness further amplifies the effects of systemic risk within the interbank market. The results have also shown that central clearing might increase the possibility of systemic liquidity risk due to tight margin requirements and the timing of cash flows required from banks. Results have also shown that haircut levels affect the possibility of systemic liquidity risks, and highlight the potential role of a market maker of last resort in limiting this possibility. The findings from Chapter 3 have far-reaching implications. This chapter sheds light on one of the overlooked side effect of margin requirement regulations that were enacted in the aftermath of the global financial crisis. It hints to regulators the importance of striking the balance between limiting counterparty credit risk through tight margin requirements, and the side effect of increasing the possibility and magnitude of systemic liquidity crises.

Chapter 4 has developed an innovative framework for a macroprudential stress test, that explicitly links liquidity risk and solvency risk of banks, as well as account for interconnectedness among them. This chapter has introduced *DistressRank* as a new measure of systemic distress which fully captures the interbank network topology and provides an innovative way to incorporate interconnectedness between banks into the stress test design. The stress test has utilised two stress scenarios, where the first is designed to assess the resilience of the banking system to macroeconomic shocks, and the second is designed to assess the possibility of amplifying endogenous shocks within the banking system and transmitting them to the macroeconomy. Chapter 4 has presented various insights for macroprudential policy making. First, the proposed stress test can be used to effectively identify the systemic vulnerability of individual banks and the resilience of the system as a whole to economic risks. Second, it can also be effective for monitoring and assessing systemic interdependencies among banks. Thus, the proposed stress test provides an effective tool for the banking system supervisors to analyse the current state of the system stability and to monitor the evolution of contagion and systemic risk within the system.

5.3 Limitations

While this thesis presents very strong results and a range of implications for macroprudential policy and regulatory oversight of banks, a critical assessment and review of the chosen methods and techniques is in order.

- The measure of risk-adjusted profitability of banks employed in Chapter 2 is expected to influence the results on the impact of securitisation on bank stability. Therefore, two different ways have been used to estimate risk-adjusted profitability, in which the individual profitability and risk measures have been selected in a way that ensures they are relevant and comparable to each other. In particular, the risk-adjusted profitability has been estimated separately for the loan portfolio and the overall balance sheet level.

- Using a rolling-window to estimate *S–score* as a measure of the net impact of securitisation on bank stability has meant using limited amount of data for the underlying estimates. This might affect the power of estimation of the coefficients used to calculate the *S–score* for individual banks and at the banking system level. Nevertheless, these estimates are in line with the overall estimate obtained from using the full sample.

- The analysis of the role of monetary policy in mitigating the impact of securitisation on bank stability has relied on measures of short-term interest rates (Bernanke and Blinder, 1992), which effectively ignores the role of unconventional monetary policy including quantitative easing in the aftermath of the global financial crisis. It is therefore advocated in Section 5.4 that future research is advisable to extend the analysis to include the effects of unconventional monetary policy on securitisation activities following the crisis.

- To ensure tractability, the agent-based model presented in Chapter 3 has considered only one channel of contagion, namely liquidity hoarding in the the interbank. Nevertheless, the global financial crisis has highlighted that different channels of contagion can be active at the same time. For example, banks might be inclined to draw on other sources of short term funding besides interbank borrowing during episodes of elevated distress. This might include selling some of their assets, and collectively lead to activating the asset fire sales channel of contagion.

- Given that the focus of the model presented in Chapter 3 is on the OTC derivatives markets, the data available to implement this model have been limited by the low transparency and public availability of information on these markets. The model, therefore, was calibrated based on publicly available data, as compared to being completely implemented using real data. Although this approach is widely used in the literature on systemic risk, using a full set of real data would have resulted in much more reliable estimates.[1] Therefore, a note of caution is appropriate when drawing inferences based on the estimates of this model.

- The model presented in Chapter 3 represents the interbank and derivatives markets as a multilayer network and assumes that both layers of this network can be represented by core-periphery network structure. Although this assumption is widely accepted in the systemic risk literature (Anand et al., 2018), some exercise with other network structures might be warranted. As a result, the model in Chapter 3 has already taken some steps in this direction by relaxing some of the assumptions behind the core-periphery structure utilised to represent the market network in the model.

- In Chapter 4, the proposed measure for systemic distress (*DistressRank*) relies on a dynamic matrix of distress, which in turn is estimated using the liquidity coverage ratio of banks. Given the complexity of calculating this ratio and the confidentiality of most of the data used to calculate it (Basel Committee on Banking Supervision, 2013*b*), we rely on the publicly available bank disclosures of this ratio. However, disclosure requirements of this ratio has only become mandatory recently. Effectively, this limits the time series of data available to estimate the *DistressRank* measure.

- The stress test presented in Chapter 4 was implemented based on a reconstructed network of interbank exposures. Although this is widely accepted in the systemic risk literature (Cocco et al., 2009), and was sufficient to highlight the merit of the proposed stress test framework, the availability of granular bank data would further increase the robustness of the analysis.

[1] To check the validity of the model estimates, the author, together with Simon Wolfe and Enrico Gerding, have implemented the model as a case study on the market turmoil that followed the Brexit vote in June 2016 in the UK. The results of this analysis have been reported in a separate paper currently under review for publication: Bakoush, M., Gerding, E. and Wolfe, S., 2017. Interest Rate Swaps Clearing and Systemic Risk.

In particular, data on bilateral exposures can be very useful to avoid the estimation errors that result from reconstructing these exposures.

5.4 Directions for Future Research

The following areas are identified as promising avenues for future research:

- The results of this thesis have provided an evidence on the influencing role of conventional monetary policy in determining the impact of securitisation on bank stability. Further research can be done to investigate the impact of unconventional monetary policy such as quantitative easing on securitisation markets. A more general line of research can focus on the link that securitisation creates between the financial system and the real economy through credit creation and how this would ultimately affect economic and financial stability.

- Since contagion can spread through different channels simultaneously as evident from the recent financial crisis, further research should be conducted to understand the interaction between different channels of financial contagion, such as liquidity hoarding and deleveraging, and to explore the impact of this interaction on the emergence of systemic risk. This would be useful in designing defence lines in the financial system as a precaution for when crises hit.

- This thesis has attempted to advance the relatively new and promising area of macroprudential stress testing by taking a systemic view of the interaction between liquidity and solvency risks. Still, more is needed to be done. One area of advancement is to make these tests truly macroprudential by considering other parts of the financial system besides banks including asset managers, insurers, and central counterparties. It is also necessary to conduct research on how to incorporate the changing behaviour of financial institutions during stress time into the design of the stress test.[2]

- A new wave of financial innovation, FinTech, has developed rapidly in the aftermath of the 2008 global financial crisis in a way that is changing the nature of financial markets, services, and institutions. In this new era, threats to both financial and monetary stability become more prevalent, which presents fresh challenges for regulators (Financial Stability Board, 2017). Therefore, there is a need for conducting research to understand the impact of FinTech on the business models of traditional financial institutions, whether (how) they adapt in response, and ultimately how FinTech would impair or enhance financial stability. Research is also needed to understand the impact of FinTech on the traditional fractional reserve banking model, and ultimately the effectiveness of the monetary policy transmission mechanism. It might also be necessary to consider who should manage the systemic FinTech risk, and whether a modern central bank should consider taking a third mandate of guarding *FinTech Stability*.

- From a methodological perspective, the theory of complex systems has been shown to be promising in studying complex financial and economic systems. Nevertheless, given the profound role that behaviour plays in economics studies, and the inherent connectivity between economic agents, there is a need to study the network dynamics of connected behaviours (Namatame and Chen, 2016). In other words, further research should be directed to understand the interaction between network topology and agents interactions. These class of models that can study topology and behaviour simultaneously would make a sizeable advancement in the fields of finance and economics

[2] Indeed, discussions between the author and some Economists at the International Monetary Fund and some central banks have shown big interest from macroprudential regulators in such extensions. It is also worth mentioning that some of these research ideas are on the research agenda of the author.

given the difficulty of separating the dynamics of a network (topology) from the dynamics on a network (behaviour).

5.5 Concluding Remark

I am very glad to have conducted my doctoral research on this topic. I believe this thesis has greatly contributed to my knowledge and understanding of Financial Economics. I hope my contributions will help advance knowledge in the area of financial stability. The field is still rich, with many open research questions waiting to be addressed and with benefits to reap. I now have in mind far more and even better questions than what I started with, and I look forward to a fruitful future in this fascinating field of research.

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