Systemic Risk: Overlapping Portfolios, Diversification and Policy Interactions

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I, Banwo O. Opeoluwa, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the work.

Abstract

Systemic risk, the possibility that a triggering event such as the failure of a large financial firm will seriously impair financial markets and harm the broader economy, has taken centre stage since the recent global financial crisis. In the wake of the crisis, policy-makers worldwide have recognised the need to fill gaps in our understanding of the dynamics of the financial system, its non-linear relationship with the real economy, and the factors responsible for alternating phases of stability and instability characterising the system. This thesis addresses the aforementioned gaps under three main headings related to systemic risk: overlapping portfolios, risk diversification and policy interaction. The insights developed suggest that specialised financial institutions pose a great risk to the stability of the financial system when banks are indirectly connected via overlapping portfolios. Furthermore, this work shows that diversification serves multiple roles in relation to financial stability; on the one hand diversification reduces the risk of an isolated bank failure, but on the other hand it increases the risk of many joint failures. The findings of the analyses are used to propose regulatory policies for improving financial stability and social welfare. Lastly, in a bid to avoid the fallacy of composition risk that is associated with the study of regulatory policies in isolation, this thesis also attempts to identify the complex interactions of resolution, monetary, and macro-prudential policies.

Impact Statement

This thesis provides financial policy makers with a set of tools for predicting the occurrence of a financial crisis and policy insights for guiding the economy in the event of a crisis. In particular, this thesis sheds light on the impact of heterogeneity in the overlapping portfolio network been financial institutions. The insights developed can be used to address one of the major drawbacks of the Basel accords in ignoring the role of diversification for setting capital requirements. Moreover, this work proposes a framework for assigning capital requirements capable of improving financial stability in relation to the existing models. In addition, regulatory policies that can improve the resilience of the financial system without imposing additional capital requirements on banks are proposed. Further, this work highlights possible unintended consequences of combining various policy instruments that may contradict and conflict with the desired objective of the regulator. Finally, the non-linear framework proposed in this thesis may help policy makers understand the true consequences of diversification on financial stability and social welfare.

Acknowledgements

As I reflect upon the wonderful and challenging experiences of my PhD work, there are a number of people that flash across my mind who made this work a reality. I feel greatly indebted to them for their support, encouragement and guidance at various stages of the process.

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Contents

Journal Publications

- Banwo, O., Caccioli, F., Harrald, P., & Medda, F. (2016). The effect of heterogeneity on financial contagion due to overlapping portfolios. Advances in Complex Systems, 19(8), 1650016. https://doi.org/10.1142/S0219525916500168
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Working Paper

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Chapter 1

Introduction

U.S. house prices rapidly rose relative to consumer price inflation, rents, and median family income between 1998 and 2006 (Bullard et al. 2009). Bernanke (2005) and Caballero et al. (2008) attribute the rapid growth to large capital inflows while Taylor (2009) discuss the role of loose monetary policy in fuelling the housing boom. During this period, the share of non-prime loans also increased rapidly (DiMartino and Duca 2007). Mortgage loans provided to borrowers with high default risk such as home buyers with low income-to-loan ratios are typically classified as non-prime. Non-prime loans performed well at the time because increasing house prices meant borrowers were able to refinance or sell their houses at higher prices (Bhardwaj and Sengupta 2009). This incentivised banks and other financial institutions to create several innovations in the mortgage market (such as collateralised debt obligations - CDOs) to facilitate large purchases of these loans. Unfortunately, house price began to decline in 2006 and borrowers found it difficult to repay their loans. This situation rapidly escalated leading to sharp increases in foreclosures and loan defaults as shown in Figure 1.1. By late 2007, several banks and financial firms had begun incurring significant losses from their investments in the mortgage market. Consequently, major financial institutions such as Fannie Mae, Freddie Mac, Bear Stearns, Lehman Brothers etc. either failed or came close to failing but for the intervention of the U.S. Department of the Treasury. This turmoil - originating from U.S. housing market, eventually led to the 2007 economic recession that crippled economies worldwide. The crisis highlighted the significance of sys-

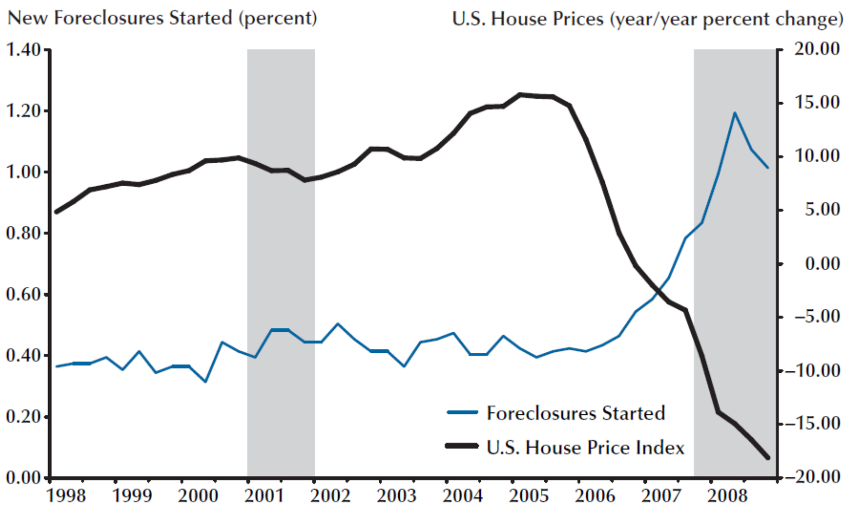


Figure 1.1: U.S. house prices and foreclosures [1].

temic risk and exposed the inherent limitations of existing regulatory frameworks for understanding the circumstances that tip the financial system from stability to instability and its non-linear interaction with the real economy. Systemic risk is the risk that a triggering event, such as the failure of a large financial firm, will seriously impair financial markets and harm the broader economy (Bullard et al. 2009). Existing economic models failed to predict the occurrence of the crisis and also left policy makers clueless on what policies to implement in-order to guide the economy out of recession (Krugman 2011; Stiglitz 2011). As such, there is a growing consensus for a complete paradigm shift from the existing frameworks to models that treat the economy as a complex evolving system (Farmer and Foley 2009; Iori and Porter 2018; Tesfatsion 2005). Jean-Claude Trichet (2010), President of the European Central Bank at the time, captures this situation concisely by noting that "...when the crisis came, the serious limitations of existing economic and financial models immediately became apparent. Macro-models failed to predict the crisis and seemed incapable of explaining what was happening to the economy in a convincing manner. As a policy-maker during the crisis, I found the available models of limited help. In fact, I would go further: in the face of the crisis, we felt abandoned by conventional tools..." In the same spirit as these remarks, this thesis studies dy-

[1] Image reproduced from (Bullard et al. 2009)

namics underlying the emergence of systemic risk under three major themes namely overlapping portfolios, risk diversification and policy interactions. This was done by employing agent-based and network modelling techniques in order to adequately capture non-linear phenomena characterising a systemic financial crisis.

1.1 Research Objectives

The goal of this thesis is to provide insights into the dynamics underlying the emergence of systemic financial crisis and develop mitigating regulatory policies. In the following sections, I elaborate on the research objectives under three research themes namely overlapping portfolios, risk diversification and policy interactions.

1.1.1 Overlapping Portfolios

Overlapping portfolios refer to indirect connections between financial firms due to similar asset investments (Caccioli et al. 2014; Caccioli et al. 2015; Huang et al. 2013). These connections serve as a contagion channel for the propagation of mark-to-market portfolio losses to one or more financial institutions - due to depression in asset prices resulting from fire sales by a distressed institution holding the same assets. In some cases, these losses may be sufficient to cause additional institutions to become distressed thereby resulting in more rounds of asset fire sales and further depression in asset prices. The 2007 quant crisis, for instance, was caused by a similar scenario in which the rapid liquidation of the portfolio of one equity hedge fund depressed prices of assets held by other funds causing them to embark on additional rounds of selling which depressed asset prices even further and resulted in large portfolio losses (see Khandani and Lo 2007, for an elaborate discussion).

Unfortunately, existing studies on overlapping portfolios have relied on the assumption of homogeneity in the degrees and sizes of banks. However, empirical findings show that real financial networks deviate from this assumption (Boss et al. 2004; Braverman and Minca 2014; Guo et al. 2015; Marotta et al. 2015; Masi and Gallegati 2012). In particular, they provide evidence that bank degrees and sizes follow heterogeneous distributions. Hence, our goal is to generalise existing work to account for these features in-order to provide insights into the systemic risk contribution of different types of banks with varying degrees and sizes. Based on the insights developed, I will proceed to study the effectiveness of existing capital policy models in relation to improving financial stability. Lastly, I will leverage on network correlation theory to investigate the possibility of reducing systemic risk without imposing new capital requirements.

1.1.2 Risk Diversification

Banks are increasingly diversifying their balance sheets across several instruments in order to reduce their individual riskiness. A major motivation for the increasing similarity is rooted in the standard financial and perhaps intuitive diversification advice "Don't put all your eggs in one basket". Indeed, the seminal work of Markowitz (1952) on portfolio selection provides evidence that diversification across various asset classes reduces the aggregate risk of a bank's portfolio. It is thus reasonable to conclude that if each bank becomes less risky due to diversification then the financial system as a whole should become more stable. Moreover, several reports before the financial crisis found little evidence for a systemic breakdown of the financial system owing to the high diversification levels at individual banks due to the extent of financial innovation (Bartram et al. 2007; Elsinger et al. 2006; Furfine 2003). However, the financial system still came close to near collapse even though banks, especially the big ones, had become largely diversified. This conundrum on the true consequences of diversification, particularly as it affects the stability of the financial system and the wider economy has prompted serious discussions from policy makers and academics.

This thesis will shed light on this conundrum by developing an agent based model in which risk is endogenously produced from an evolving stylised system. This approach deviates from network modelling techniques in which the underlying dynamics is based on assumptions of exogenous shocks and static network structures. However, specifying shocks ex-ante neglects the fact that economic and financial shocks endogenously emerge from complex interactions. Further, our approach provides an opportunity to see if the financial system can endogenously display the "robust-yet-fragile" property popularly reported in the literature (Caccioli et al. 2014; Gai and Kapadia 2010; Mistrulli 2011). Also, I will investigate the stability impact of preferential lending relationships between banks and firms described in (Marotta et al. 2015; Masi and Gallegati 2012). Finally, I will use our model to investigate the possibility of designing policies that endogenously permit diversification without exacerbating systemic risk.

1.1.3 Policy Interactions

The financial crisis precipitated calls for additional policy overlays to improve the stability of the financial system. However, combining these policy instruments with existing regulatory policies could contradict and conflict with the desired objective of the regulator and may even lead to unintended consequences on the financial system. As such, addressing this challenge has become imperative for policy makers, who are left with no other choice but to base their decisions on common sense and anecdotal analogies to previous crisis (Farmer and Foley 2009). Unfortunately, regulatory policies have mostly been studied in isolation until recently thus bearing the fallacy of composition risk (Angelini and Clerc 2011; Boissay 2011; Cosimano and Hakura 2011; Derviz 2013; Dib 2010; Gauthier et al. 2012; Miles et al. 2013; Ryo et al. 2010; Slovik and Cournède 2011).

I address this challenge by studying the long-term impact of the resolution tool used in resolving failed banks in the presence of monetary and macroprudential policies using an agent based model that couples the real economy and a financial system. I will model a central bank agent that uses a monetary rule that indexes interest rate relative to changes to one or more economic conditions namely inflation, unemployment & credit volume. Further, I will consider Basel II and Basel III regulatory frameworks as the possible macroprudential tools while bailout, bail-in and P&A (purchase & assumption) are the possible instruments available to the central bank for resolving failed banks.

1.2 Thesis Contribution

In this section, I briefly discuss the contribution of this thesis to the literature on systemic risk - in relation to the research themes considered in this thesis namely overlapping portfolios, risk diversification and policy interactions.

The work on overlapping portfolios reveals that if banks have a heterogeneous degree distribution the system becomes less robust with respect to the initial failure of a random bank, and that targeted shocks to the most specialised banks (i.e. banks with low degrees) increases the probability of observing a cascade of defaults. In contrast, a heterogeneous degree distribution for assets increases stability with respect to random shocks, but not with respect to targeted shocks. Also, assigning capital to banks in relation to their level of diversification reduces the probability of observing cascades of defaults relative to size based allocations. Finally, a non-capital based policy that improves the resilience of the system by introducing disassortative mixing between banks and assets is proposed.

I then investigated the consequences of diversification on financial stability and social welfare. To do this, an agent based model that couples the real economy and a financial system is developed - by building on micro-behaviours described in (Delli Gatti et al. 2011; Gualdi et al. 2015; Klimek et al. 2015; Poledna and Thurner 2016). I show that the model can reproduce several stylized facts reported in real economies. We find that the risk of an isolated bank failure (i.e. idiosyncratic risk) is decreasing with diversification. In contrast, the probability of joint failures (i.e. systemic risk) is increasing with diversification which results in more downturns in the real sector. This finding is important because it kicks against the traditional reasoning that if each bank becomes less risky due to diversification then the financial system as a whole should become more stable. It is this kind of reasoning that brought false beliefs that the financial system was highly robust before the advent of the financial crisis. We find that the system displays a "robust yet fragile" behaviour particularly for low diversification. Moreover, introducing preferential attachment into the lending links of the bank-firm network does not change the risk profiles produced by the original model. However, preferential attachment increases idiosyncratic risk but significantly reduces system risk in the financial system. Finally, I show that a regulatory policy that promotes bank-firm credit transactions that reduce similarity between banks can improve financial stability whilst permitting diversification.

Lastly, I provide insights into the long term economic impact of different bank resolution instruments used by regulators to resolve a failed bank in the presence of prevailing monetary and macroprudential policies. We find that Basel III does not always improve the stability of the financial system relative to Basel II. Specifically, Basel III produces more bank defaults when the central bank follows an inflation targeting monetary rule but reduces the frequency of defaults if the monetary policy rule also responds to changes in unemployment and credit volume. Further, a bailout resolution strategy results in the most frequent bank defaults while the lowest occurrence of bank defaults is achieved in a P&A regime for all combinations of monetary and prudential policies. Also, I investigated the contribution of each Basel III component and find that the performance of Basel III framework is mainly characterised by the capital adequacy ratio and conservation buffer components while the additional constraint imposed by leverage requirement does not seem to have any reasonable impact on the performance of the framework. Moreover, the additional capital overlay Basel III components do not appear to be addictive under a P&A regime.

1.3 Thesis Structure

The structure of the remaining parts of this thesis is presented in Figure 1.2. Further, in the following paragraphs, I provide a brief description of each chapter and its logical relationship with the rest of the thesis.

In Chapter 2, I present a review of relevant research work on systemic risk associated with the objectives of this thesis. The subsequent chapters extend this review by referencing pertinent literature within the context of their applicable areas. A general overview of the methodology considered in this thesis is presented in Chapter 3 - implementation details are however provided in subsequent chapters.

Chapter 4 couples agent based modelling techniques and network theory in order to study the systemic risk posed by indirect connections associated with overlapping portfolios between financial institutions. It has become necessary to model

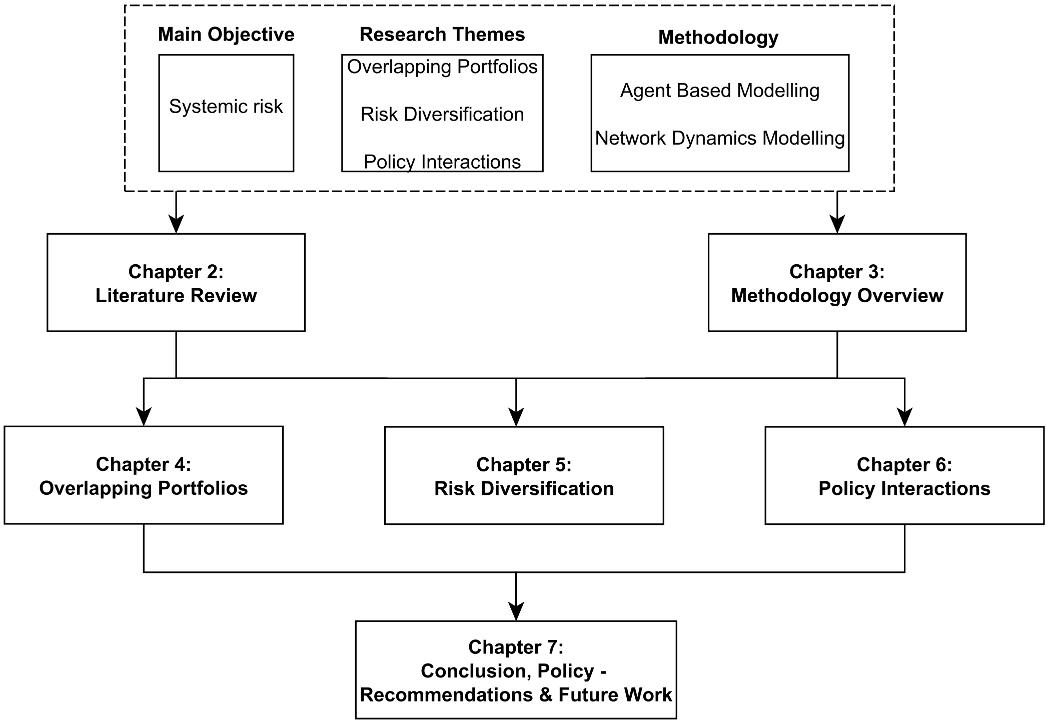


Figure 1.2: Thesis Structure

these connections because they serve as a key contagion channel for the propagation of losses to one or more financial institutions due to depression in asset prices resulting from fire sales by a distressed institution holding the same assets. A key message from our findings is that specialised institutions (i.e. institutions who hold significant amounts of specific assets) such as mortgage banks, building and loan associations, specialist funds etc. pose a great risk to the stability of the financial system. Our exploration of possible mitigating policies reveals that assigning capital to banks in relation to their level of diversification reduces the likelihood of having a systemic financial crisis. An even deeper analysis shows that encouraging dissortative mixing between banks and assets can improve financial stability without imposing additional capital requirements. Although, the framework presented in Chapter 4 captures some important dynamics of the financial system highlighted during the crisis and enables the evaluation of regulatory policy responses. However, its underlying dynamics is based on assumptions of exogenous shocks. Specifying shocks ex-ante neglects the fact that economic and financial shocks endogenously emerge from complex interactions.

Chapter 5 breaks away from this mechanistic approach by explicitly considering an agent based model that couples the real economy and a financial system. Here, I provide emergent profiles of the consequences of diversification on financial stability and social welfare. A central message highlighted in this chapter is that diversification serves multiple roles; on one hand it reduces the risk of an isolated bank failure (i.e. idiosyncratic risk) but on the other hand it increases the risk of joint failures (i.e. systemic risk). The chapter provides key insights towards appropriate regulatory responses. Specifically, I show that a regulatory policy that promotes bank-firm credit transactions that reduce similarity between banks can improve financial stability whilst permitting diversification.

The agent based model considered in Chapter 5 is deliberately simplified in-order to understand the dynamics governing the behaviour of the financial system and its interaction with the real economy. However, this approach neglects the impact of joint regulatory responses since policies are studied in isolation and thus bears a fallacy of composition risk. Chapter 6 addresses this challenge by extending the agent based model considered in Chapter 5. In particular, Chapter 6 sets out to understand the long term economic impact of different bank resolution instruments used by regulators to resolve a failed bank in the presence of prevailing monetary and macroprudential policies. A key message is that combining new policies with certain prevailing policies may not necessarily be beneficial. For instance, combining the new Basel III framework recently proposed by the Basel Committee on Banking Supervision (BCBS) with an inappropriate monetary policy will not improve the stability of the financial system. In fact, it would further contribute to the risk of the systemic breakdown of the system.

Chapter 2

Literature Review

The concept of systemic risk has become highly pronounced since the recent global financial crisis. Regulatory bodies around the world realised that they lacked a true understanding of the dynamics underlying the emergence of risk from the financial system and the feedback consequences on the real economy. This situation has led to a surge in the number of research work targeted at identifying sources of systemic risk and channels through which risk spreads through the system. This thesis addresses three major themes associated with systemic risk namely overlapping portfolios, risk diversification and policy interactions. As such, this chapter highlights relevant work that also address these systemic risk areas.

2.1 Overlapping Portfolios

Overlapping portfolios refers to indirect connections between financial institutions that serve as a contagion channel for the propagation of mark-to-market portfolio losses to one or more financial institutions due to depression in asset prices - resulting from fire sales by a distressed institution holding the same assets. In some cases, these losses may be sufficient to cause additional institutions to become distressed thereby resulting in more rounds of asset fire sales and further depression in asset prices. Despite its significance, the literature is widely focused on the role of counterparty and roll-over risks in propagating contagion (Allen and Gale 2000; Caccioli et al. 2011; Gai et al. 2011; Hałaj and Kok 2014; Iori et al. 2006). Further, existing studies on overlapping portfolios have relied on the assumption of homogeneity in the degrees and sizes of banks. However, empirical findings show that real financial networks deviate from this assumption (Boss et al. 2004; Braverman and Minca 2014; Guo et al. 2015; Iori et al. 2008; Marotta et al. 2015; Masi and Gallegati 2012)

For instance, Cifuentes et al. (2005) study the impact of overlapping portfolios by considering two channels of contagion in a stylised system of interconnected financial institutions including direct counterparty connections and a layer of common asset holdings. The financial institutions are subject to regulatory constraints and follow mark-to-market accounting rules. Liquidity risk is captured in their model by a market impact function that results in the depression of illiquid assets when the demand for such assets is not perfectly elastic. They show that marking the prices of assets to market can result in cascade of portfolio of losses which may be sufficient to cause one or more financial institutions to become distressed thereby resulting in more rounds of asset fire sales and further depression in asset prices. Further, they find that a regulatory policy that imposes liquidity requirement on financial institutions can be as effective as setting capital requirements in addressing systemic externalities stemming from the network layer of common asset holdings. In a similar work, Nier et al. (2007) study the impact of liquidity risk on financial contagion due to overlapping portfolios in a stylised financial network of interbank linkages. Similar to Cifuentes et al. (2005) liquidity risk arises in their model from depression of asset prices due to forced sales of illiquid assets. They find that this aggravates the likelihood of a systemic breakdown of the financial system irrespective of its level of average interbank connectivity and total amount of capital. Moreover, they show that the impact of liquidity risk becomes more pronounced as the financial network becomes more concentrated. Further, Iori et al. (2006) show that the interbank network - mainly overnight can have destabilizing consequences on the financial system when banks have heterogeneous liquidity reserves.

In a related work, Arinaminpathy et al. (2012) study the importance of big and highly connected banks on financial stability and regulatory responses using a unified model of the financial system that captures three channels of contagion namely liquidity hoarding, asset price depression due to overlapping portfolios and losses due to direct linkages in a counterparty network. Their model also includes a distinct feature that captures the aggregate confidence in the system. They show that large, well connected banks result in non-linear devastating impact on the stability of the system. In agreement with the findings reported by Nier et al. (2007), they further show that this effect becomes more pronounced with higher network concentration. Moreover, they show that the resilience of the system improves when big banks are subject to higher capital requirements relative to small banks. Gai and Kapadia (2010) adopt the market-impact function proposed by Cifuentes et al. (2005) in order to study the impact of asset fire sales in a stylised financial system of overlapping portfolios imposed upon a network layer of direct counterparty exposures. They also show that including fire sales dynamics widens the region within which contagion occurs with non-zero probability. May and Arinaminpathy (2010) further show that this effect becomes more pronounced with increasing interbank recovery rates. The relationship between asset fire sales and credit freeze-up during a financial crisis is stressed in the work by Diamond and Rajan (2011). They also propose alternative effective regulatory policies for resolving failed banks at minimum cost to the tax payers.

Unfortunately, the models discussed so far only consider a single asset class in their contagion channel due to overlapping portfolios which is far from reality. Caccioli et al. (2014) addresses this limitation by generalising the model proposed by Cifuentes et al. (2005) to a multi-asset case. They study the stability features of financial contagion due to overlapping portfolios in a stylised model of the financial system consisting of a bipartite network of banks and assets. They characterise the stability of the financial system in terms of leverage, diversification, market impact and asset crowding. In their model, systemic risks is defined as the probability of observing a global cascade of bank defaults. Their analysis reveals that the system undergoes two phase transitions with increasing diversification between which global cascades can occur. Further, they find a critical leverage value below which the system is generally stable for a given average diversification value and above which global cascades can occur with non-zero probability. However, their approach relies on the assumption of homogeneity in the degrees and sizes of all banks which may not necessarily be the case. In fact recent empirical studies (Braverman and Minca 2014; Guo et al. 2015; Marotta et al. 2015; Masi and Gallegati 2012) show that real financial networks of common portfolio holdings and balance sheet size distributions deviate from this assumption. Specifically, they provide evidence of a power law in these distributions.

Complementary views on these findings are also reported by several empirical studies. Huang et al. (2013) propose a stress test model for systemic risk propagation in bipartite network of banks and assets. Using a large dataset of 2007 US commercial banks' balance sheet data, they validate their model in terms of its ability to identify banks that failed in the wake of the financial crisis. Similar to the findings reported by Caccioli et al. (2014), they show that the system undergoes alternating phases of stability and instability depending on the network parameters. In another empirical study, Caccioli et al. (2015) analyse the impact of overlapping portfolios of banks on financial stability using a stylised multi-layered network model of the financial system using a dataset of balance sheet and interbank exposures detail of the Austrian financial system. Interestingly, they show that counterparty risk on its own results in a fairly stable system. However, the combined impact of counterpart risk and overlapping portfolio risk results in more cascading bank failures. Similarly, Langfield et al. (2014) provides a comprehensive empirical study of the UK interbank network using a new dataset containing granular data of exposures in key markets. They group the markets into two networks i.e. interbank exposures network and interbank funding network, thus allowing for the propagation of credit and liquidity risk through the system. They show that the network approximates a core-periphery structure depending on the asset classes. Further, they find as in (Freixas and Holthausen 2005) that certain core banks can act as fire-stops to contagious defaults depending on their level of diversification. Their finding lends further credence to the call for increased capital surcharges for systematically important banks required to build more resilience into the system.

A study of the cross-sectional aspects of systemic risk arising from overlapping portfolios is provided by Kok (2013) using a multi-layered interbank network based on a sample dataset of 50 large EU banks at the end of 2011. The network captures three interbank relationships namely the short-term exposures, long term bilateral exposures having maturities greater than 3-months and a network of common exposures to security portfolios. They show that the feedback impact of an exogenous shock is substantially much larger than when each network layer is considered in isolation. In particular, they find that studying an interbank layer in isolation can lead to serious underestimation of financial contagion. Pickett (2014) extends the stress test network model to include interbank collateral exposures and an integrated agent based framework. The agent based model endows banks with behavioural features to react to shocks on their balance sheets. Similar to Kok (2013), they show that combining several layers of interbank exposures can have substantial consequences on the estimation of contagion-induced losses. The paper further provides a practical framework for conducting stress test and Value at Risk analysis at individual bank levels. In a related work, Webber and Willison (2011) adopt a multi-layered exposures network structure to study the impact of capital requirements on financial stability using datasets of five major UK banks. They propose a framework that achieves a policy-maker's target for the overall system solvency by solving an optimisation problem to determine the optimal capital requirement for each bank. They approach encapsulates a structural credit model to capture the evolution of the banks' balance sheets. In particular, a bank's asset evolution is modelled as in (Merton 1974). The network is cleared using the approach proposed by Eisenberg and Noe (2001) if a bank defaults (i.e. the asset value falls below a predefined default threshold).

Martinez-Jaramillo et al. (2014) conduct an empirical study of the Mexican financial system network with the goal of investigating systemic risk. They study the evolution of systemic risk in the payment and interbank exposures network with traditional network centrality measures and several non-topological properties for characterizing individual bank behaviour. They further propose a unified measure of interconnectedness that can be used to determine systemically relevant nodes based on principal component analysis. Building on this work, Solorzano-Margain et al. (2013) have further conducted a study on financial contagion using an extended dataset of the Mexican exposures network. They show that filling missing data using the maximum entropy principle typically leads to underestimation of contagion risk. In the light of this finding, Anand et al. (2015) propose an alternative method for estimating counterparty exposures. Unlike the maximum entropy their minimum density approach assigns the largest exposures to the most probable nodes. As such, contagion is overestimated in their model. However, they show that combining their method with the maximum entropy principle approximates the true interbank network better than the existing approach. In a more recent work, Poledna and Thurner (2016) study the systemic risk contribution due to four layers of exposures in the Mexican banking system in the 2007-2013 period. In agreement with previous studies, they show that studying a network layer in isolation results in severe underestimation of systemic risk. They further show that exposures associated with overlapping holdings of securities constitute crucial components in the estimation of systemic risk on national scales.

Table 2.1: Literature Summary: Overlapping Portfolios

Authors	Analytical Framework	Datasets	Main Finding
Cifuentes et al. (2005)	Theoretical	-	Mark to market accounting rules can result in portfolio of losses that may trigger a cascade of defaults across the system
Nier et al. (2007)	Theoretical	-	Overlapping portfolios aggravates the likelihood of a systemic breakdown of the financial system irrespective of its average level of connectivity and aggregate capital
Gai and Kapadia (2010)	Theoretical	-	Associate overlapping portfolios with a fire sales dynamic that widens the region within which contagion occurs with non-zero probability
May and Arinaminpathy (2010)	Theoretical	-	Higher interbank recovery rates aggravates the devastating impact of overlapping portfolios.
Iori et al. (2006)	Theoretical	-	Interbank network can amplify financial contagion and increased defaults when banks have heterogeneous liquidity reserves

Table 2.1: Literature Summary: Overlapping Portfolios

Authors	Analytical Framework	Datasets	Main Finding
Arinaminpathy et al. (2012)	Theoretical	-	Large, well connected banks have non-linear devastating impact on the stability of a multi-layered financial system
Diamond and Rajan (2011)	Theoretical	-	Relationship between asset fire sales and credit freeze-up during a financial crisis
Caccioli et al. (2014)	Theoretical	-	Financial system undergoes two phase transitions of stability and instability in a multi-asset bipartite financial network
Huang et al. (2013)	Empirical	US Commercial banks 2007 balance sheets	Propose a stress test framework for assessing systemic risk in a bipartite network of banks and assets
Caccioli et al. (2015)	Empirical	Austrian banking system (2006-08)	Combined impact of counterpart risk and overlapping portfolio risk results in more cascading bank failures
Langfield et al. (2014)	Empirical	UK interbank data	Core banks can act as fire-stops to contagious defaults depending on their level of diversification

Table 2.1: Literature Summary: Overlapping Portfolios

Authors	Analytical Framework	Datasets	Main Finding
Kok (2013)	Empirical	Sample of 50 large EU banks (last quarter of 2011)	Considering an interbank exposures layer leads to severe underestimation of financial contagion
Pickett (2014)	Empirical	FR Y-9C top 10 US banks' balance sheets	Collaterals backing interbank lendings pose a systemic risk associated with fire sales and margin calls.
Webber and Willison (2011)	Empirical	Balance sheet data of 5 major UK banks (2004 H1 - 2009 H1)	Proposed framework for assigning capital requirements to reduce systemic risk due to network effects
Martinez-Jaramillo et al. (2014)	Empirical	Mexican interbank network: Daily exposures (03/01/2005 - 31/12/2010)	Characterise systemic relevance of banks in the multi layered exposures financial network
Solorzano-Margain et al. (2013)	Empirical	Mexican financial system: monthly exposures (07/2008-12/2010); daily exposures (01/2011-08/2011)	Estimating exposure networks based on maximum entropy principle underestimates financial contagion

Table 2.1: Literature Summary: Overlapping Portfolios

Authors	Analytical Framework	Datasets	Main Finding
Gabbi et al. (2015)	Theoretical	Non-monotonic relationship between banking performance and degree of connectivity of the interbank market	
Poledna and Thurner (2016)	Empirical	Mexican banking system (2007 - 2013)	Overlapping holdings of securities constitute crucial components for estimating systemic risk on national scales

2.2 Risk Diversification

Diversification has been known to reduce the idiosyncratic risk of a financial institution since the seminar work of Markowitz (1952) on portfolio selection, however, institutional diversification promotes interconnectedness amongst institutions which may contribute to the fragility of the system during a crisis. For instance, the financial system still came close to near collapse even though banks, especially the big ones, had become largely diversified. This conundrum on the true consequences of diversification, particularly as it affects the stability of the financial system and the wider economy has prompted serious discussions from policy makers and academics in a growing number of studies.

The reports by Wagner (2008) and Wagner (2010) show that diversification increases the likelihood of a systemic crisis due to the homogenization of the financial system even though it is desirable in terms of reducing the probability of an individual bank failure. Wagner (2011) further consider a portfolio choice model in which higher liquidation costs endogenously arise in the event of joint failures. They show that in equilibrium investors rationally hold portfolios that maximise diversity from each other and thereby forego diversification benefits in order to avoid the risk associated with high joint liquidation cost. In contrast, Acharya and Yorulmazer (2005) and Acharya and Yorulmazer (2007) suggest that banks undertake similar activities in order to increase the probability of joint failures in such a manner that increases their chances of being bailed out by the regulator.

In a related work, Battiston et al. (2012b) investigate under what circumstances risk diversification increases systemic risk in a stylised financial network of direct credit linkages. They show that diversification does not necessarily improve the stability of the financial system even though it reduces individual risk of the financial institutions. In particular, they find that diversification can serve to amplify systemic risk in the presence of second round feedback mechanisms such as funding runs by short term lenders. Similarly, Caccioli et al. (2014) study the role of diversification on financial contagion due to overlapping portfolios and showed that the system undergoes two phase transitions with increasing diversification between which global cascades can occur. This finding is echoed by Raffestin (2014) using a theoretical model of financial contagion due to constrained asset sales by portfolio investors endowed with heuristic behaviours. They show that the optimal diversification level can either be none or high but not intermediate since such levels create inter-linkages between investors without going far enough to reduce their individual risk. They further show that the financial system becomes more resilient when investors hold more distant (i.e. uncorrelated) assets. Similarly, Gabbi et al. (2015) study the impact of various interbank structures on financial stability with an agent based model. They show that banks' performance vary in a non-monotonic way with respect to the degree of connectivity in the interbank network.

Tasca and Battiston (2011) also study the consequences of diversification on financial stability in a stylised counterparty network of banks partly holding assets external to the system such as mortgages. Similar to previous findings, they show that diversification can increase the aggregate risk of the financial system when the cash flow from the external assets is negative during downturns in the economy, but this situation is reversed in periods of economic booms. They also investigate the implications for social costs and show that a regulatory policy that encourages diversification during upturns in the economy but restricts diversification during recessions creates socially optimal results. In a recent work, Tasca et al. (2014) also show that diversification can have ambiguous consequences on the stability of the financial by studying the joint impact of leverage and diversification on financial stability using a structural risk model based on the framework proposed by Merton (1974). In particular, they find that a given leverage value can result in alternating phases of stability and instability depending on the diversification strategy.

The concept of diversification with its associated risk profiles is also related to the literature on bank herding since both concepts lead to concentrations in the same set of activities. Allen and Carletti (2006) and Allen and Gale (2005), for instance, show that credit risk transfer between the banking and insurance sector creates portfolio 'overlaps' (i.e. inter-linkages) that can increase systemic risk and have destabilising consequences on the real economy. In their model, risk arises because of mark-to-market losses suffered by banks due to the contagious depression in asset prices - induced by liquidations in the insurance sector during periods of stress. Furthermore Wagner and Marsh (2006) provides sufficient conditions for which credit risk transfer between financial institutions with varying degrees of fragility can reduce stability.

Table 2.2: Literature Summary: Risk Diversification

Authors	Analytical Framework	Main Finding
Wagner (2008)	Theoretical	Homogenization of the financial system increases systemic risk
Wagner (2010)	Theoretical	Diversification makes individual institutions more stable but increases the fragility of the financial system
Wagner (2011)	Theoretical	In equilibrium, investors forgo diversification benefits and hold maximally diverse portfolios in order to avoid high joint liquidation cost.
Acharya and Yorulmazer (2005) and Acharya and Yorulmazer (2007)	Theoretical	In contrast to Wagner (2011) show that banks undertake similar activities in order to increase the probability of government bail outs.
Iori et al. (2008)	Empirical	Provide evidence of heterogeneity in the lending relationship of banks
Battiston et al. (2012b)	Theoretical	Diversification can amplify systemic risk in the presence of second round feedback mechanisms such as funding runs
Caccioli et al. (2014)	Theoretical	Diversification causes phase transitions of stability and instability in the financial system

Table 2.2: Literature Summary: Risk Diversification

Authors	Analytical Framework	Main Finding
Raffestin (2014)	Theoretical	Financial system becomes more resilient when investors hold more distant (i.e uncorrelated) assets
Tasca and Battiston (2011)	Theoretical	Diversification can increase aggregate risk of the financial system during economic downturns but becomes beneficial during upturns.
Tasca et al. (2014)	Theoretical	A given leverage value can result in alternating phases of stability and instability depending on the diversification strategy
Allen and Carletti (2006) and Allen and Gale (2005)	Theoretical (Credit risk transfer)	Credit risk transfer between the banking and insurance sector may increase systemic risk
Wagner and Marsh (2006)	Theoretical (Credit risk transfer)	Provides sufficient conditions for which credit risk transfer between financial institutions with varying degrees of fragility can reduce stability

2.3 Policy Interactions

Central banks use several policies to regulate their financial system with some desired economic impact in perspective. However, combining these policy instruments with the existing regulatory policies could contradict and conflict with the desired objective of the regulator and may even lead to unintended consequences on the financial system. As such, addressing this challenge has become imperative for policy makers.

Unfortunately, these regulatory policies have mostly been studied in isolation until recently thus bearing the fallacy of composition risk. In particular, the literature on prudential regulation focused mostly on capital adequacy requirement *CAR* has received the widest attention from academia and industry over the last decade. Cosimano and Hakura (2011), Gauthier et al. (2012), Miles et al. (2013), Ryo et al. (2010), and Slovik and Cournède (2011) provide empirical evidence of a positive impact of the *CAR* instrument on the economy and the stability of the financial system while Angelini and Clerc (2011), Boissay (2011), Derviz (2013), and Dib (2010) have used general equilibrium/ dynamic stochastic general equilibrium based models to also investigate the qualitative impact of prudential regulation on the economy and financial stability. A growing number of recent studies have adopted the use of agent based computation models for economic/financial policy evaluation.

Aymanns et al. (2016) provide an insightful study of the implications of banks' leverage management based on historical using an agent based model of a multi-asset financial system. In their model, banks set their desired leverage target based on their perceived portfolio risk given by the computed Value-at-Risk (VaR) estimate. They show that this leverage management behaviour results in recurring bubbles and crashes of the stock price – a phenomenon commonly referred to as "leverage cycles". An agent based model is also adopted by Poledna et al. (2014) to study the dynamical feedback of leveraged investors. In their model, the investors are hedge funds subject to leverage risk management policies. They show that while Basel II regulation makes the system more stable when leverage is low, the situation is reversed when for high leverage. Their results demonstrate the pro-cyclical impact of Basel II when leverage is high. In particular, they show the destabilising impact of synchronised buying and selling of assets as a result of deleveraging actions of highly leveraged agents.

Lengnick (2013) provides a simple agent based model comprising rationally bounded agents namely households and firms. They show that interaction between the agents results in the emergence of several stylised facts reported in real economies such as alternating phases of bubbles and bursts observed in aggregate production, negative relationship between inflation and unemployment as in Philip's curve etc. Their work further provides key insights into the long/short term impact of the monetary policy of money supply on production and price. The impact of different mortgage granting policies used by banks is investigated by Erlingsson et al. (2014a) with an agent based model that not only integrates the real economy and financial system but also includes the housing market. They show that relaxed mortgage policies cause the economy to be more prone to recessions due to falling house prices. The situation becomes even worse with more permissive lending and leads to more devastating consequences on the economy. They find that this trend is reversed with stricter policies, specifically they find the economy remains stable under these conditions. In addition, they show that easier access to credit for firms leads to increasing house prices as result of the so-called households' wealth impact.

Ashraf et al. (2011) also overlay a credit market on top of an agent based model of the economy in which banks act as lenders to heterogeneous firms. The banks in their model are constrained by capital ratio requirements imposed by a regulatory body. Their model shows rare occurrences of destabilising cases emanating from the banking sector. In particular, they find that the economy is able to recover faster when the regulatory constraint imposed on banks are more loose. In a similar work, Cincotti et al. (2010) investigate the impact of lower capital adequacy ratios on the economy using the EURACE framework (a large-scale agent based platform targeted at analysing policy designs in Europe). While their results show that short run economic output increases with lower capital ratio requirements; they also find higher number of firm defaults and credit rationing in the long run.

In order to address the question on whether to bail-in, bailout or liquidate a failed financial institution Klimek et al. (2015) have adopted a simplified version of the CRISIS agent based framework that integrates the financial system and the real economy. The resolution policies are compared in terms of their impact on macroeconomic variables namely unemployment & GDP as well as on the level of transactions in the financial system. They show that the optimal resolution strategy in a low interest rate regime (i.e. in an economy characterized by low unemployment and high productivity) is to liquidate a failed institution while bail-in was shown to outperform others in a high interest rate regime i.e. for economies characterised with high unemployment and low GDP.

In the area of fiscal policy design, Dosi et al. (2010) adopt an agent based model based on Keynesian demand and Schumpeter's production functions to study the impact of fiscal policies (including unemployment benefit and tax levels) on GDP growth and volatility as well as unemployment rate. Though simple, their model is able to reproduce a number of macroeconomic stylised facts. They find that complimentary functioning of Keynesian and Schumpeterian policies impose a necessary condition for economic growth. They further extend this model in (Dosi et al. 2013) to investigate the economic impact of monetary policy i.e. changes in interest rates. In the extended model, they include banks who act as lenders in the credit market and are subject to regulatory constraints. They find that monetary policy is only effective when income distribution is low otherwise it becomes ineffective. A parallel work in this area by Cincotti et al. (2010) study the joint impact of a central bank's quantitative easing (QE) policy and the fiscal policy using an extension of EURACE framework. They show that the economy performs better as a result of more effective QE and fiscal policy, but long-run output volatility and inflation become substantially higher.

A recent trend of research work attempt to understand the interaction of alternative macroprudential tools and monetary policy. Agenor et al. (2013) employ a

DSGE model endowed with imperfect credit markets to study the joint impact of capital requirements and monetary policy on economic and financial stability. They show that combining Basel III and a monetary policy that adapts to te credit gap as well as inflation deviations promotes economic stability. Angeloni and Faia (2013) also study the impact of the interplay between monetary policy and capital regulations on financial risk. They analysis reveals that a combination of counter-cyclical Basel III capital requirements and a leverage/asset prices augmented monetary rule provides the best results. Similar findings are reported by Napoletano et al. (2015), who extend the agent based model proposed by Ashraf et al. (2011) in order to study the joint impact of alternative prudential regulation and various monetary policies on the macroeconomy and financial system. They show that a combination of Basel III and a monetary policy that considers inflation, unemployment and credit volume is the most beneficial for the economy and the financial system. Further, they show that the inclusion of the leverage component is non-addictive with the performance of the Basel III framework. In a related study, Suh (2014) compare the impact of macroprudential regulation against monetary policy. They show that monetary policy has the effect of stabilising inflation but not credit while macroprudential policy stabilises credit, but it is not effective for inflation. The findings reported in these papers share commonality with those reported by Angelini et al. (2012), Beau et al. (2012), and Spencer (2014).

Table 2.3: Literature Summary: Policy Interactions

Authors	Analytical Framework	Regulatory Policies	Main Finding
Cosimano and Hakura (2011), Gauthier et al. (2012), Miles et al. (2013), Ryo et al. (2010), and Slovik and Cournède (2011)	Empirical	Capital adequacy requirement (CAR)	CAR improves the resilience of the financial system and positively impacts the real economy
Angelini and Clerc (2011), Boissay (2011), Derviz (2013), and Dib (2010)	Theoretical (DSGE)	Capital adequacy requirement (CAR)	Provide qualitative impact of macroprudential regulation on financial stability
Ashraf et al. (2011)	Theoretical (ABM)	Capital adequacy requirement (CAR)	Economy recovers faster when the regulatory constraint imposed on banks are more loose
Cincotti et al. (2010)	Theoretical (ABM)	Capital adequacy requirement (CAR)	Lower capital requirement improves economic output in the short run but also increases credit rationing and firm defaults
Aymanns et al. (2016)	Theoretical (ABM)	Basel II (Leverage requirement)	Leverage management behaviour results in recurring bubbles and crashes of the stock price

Table 2.3: Literature Summary: Policy Interactions

Authors	Analytical Framework	Regulatory Policies	Main Finding
Poledna et al. (2014)	Theoretical (ABM)	Basel II (Leverage requirement)	Basel II is pro-cyclical
Lengnick (2013)	Theoretical (ABM)	Monetary policy	Provides key insights into the long/short term impact of the monetary policy of money supply on production and price
Dosi et al. (2013)	Theoretical (ABM)	Monetary policy	Monetary policy is only effective when income distribution is low otherwise it becomes ineffective
Erlingsson et al. (2014a)	Theoretical (ABM)	Mortgage granting policy	Relaxed mortgage policies causes the economy to be more prone to recessions due to falling house prices
Klimek et al. (2015)	Theoretical (ABM)	Bankruptcy resolution policy	Bail in is more beneficial in a high interest rate regime but purchase and assumption performs better when interest rates are low
Dosi et al. (2010)	Theoretical (ABM)	Fiscal policy	Complimentary functioning of Keynesian and Schumpeterian policies impose a necessary condition for economic growth

Table 2.3: Literature Summary: Policy Interactions

Authors	Analytical Framework	Regulatory Policies	Main Finding
Cincotti et al. (2010)	Theoretical (ABM)	Fiscal policy and quantitative easing (QE)	Economy performs better because of more effective QE and fiscal policy but long-run output volatility and inflation become substantially higher.
Agenor et al. (2013) and Angeloni and Faia (2013)	Theoretical (DSGE)	Basel III (CAR) and monetary policy	Combining Basel III and a monetary policy that adapts to te credit gap as well as inflation deviations promotes economic stability
Napoletano et al. (2015)	Theoretical (ABM)	Monetary policy and macroprudential regulations	Combining Basel III with a monetary policy that considers inflation, unemployment and credit volume is the most beneficial for the economy and the financial system
Angelini et al. (2012) and Suh (2014)	Theoretical (DSGE)	Monetary policy and macroprudential regulations	Monetary policy has the effect of stabilising inflation but not credit while macroprudential policy stabilises credit but it is not effective for inflation

Table 2.3: Literature Summary: Policy Interactions

Authors	Analytical Framework	Regulatory Policies	Main Finding
Beau et al. (2012) and Spencer (2014)	Empirical (Discussion)	Monetary policy and macroprudential regulations	Joint coordination of monetary and macroprudential policies could create complexities and result in unintended consequences

Chapter 3

Methodology: An Overview

For decades, the ”science” of setting economic and financial policy has been based on neoclassical models grounded on the theoretical framework of traditional economic paradigm. The bitter experience of the crisis, however, exposed the limitation of these models in characterising non-linear feedback and economic downturns associated with systemic risk. In fact, these models failed to predict the occurrence of the crisis and also left policy makers clueless on what policies to implement in-order to guide the economy out of recession (Krugman 2011; Stiglitz 2011).

As such, there is a growing consensus for a complete paradigm shift from the existing frameworks to models that treat the economy as a complex evolving system (Farmer and Foley 2009; Tesfatsion 2005). Trichet (2011) noted how ”the combination of complexity, interconnectedness, payments promises in debt contracts, limits of information and basic human behaviour - animal spirits” lead to the build-up of systemic vulnerabilities. In the following sections, I elaborate on the limitations of traditional economic models and provide a concise overview of the methods used in this thesis namely agent-based and network models.

3.1 Limitations of Traditional Models

In this section, I discuss the inherent limitations of traditional economic models for understanding the dynamics underlying the emergence of systemic risk and designing mitigating macroeconomic policies. Traditional economic models are typically based on dynamic stochastic general equilibrium (DSGE) methodology.

DSGE models typically consist of representative agents making rational decisions by optimizing an objective function. Such models are occasionally perturbed by random exogenous shocks in-order to simulate the stochastic evolution of the real economy.

At the core of a DSGE model is a representative household that determines its demand for produced goods by optimizing a utility function subject to constraints, a representative firm that aggregates goods produced by a set of firms - where the supply of goods is determined by a given production function, an equilibrium price vector that ensures market clearing and a regulatory agency that controls the monetary policy of the economy (i.e. interest rates). Essentially, the implementation of DSGE models for policy making follows a top-down approach that involves solving a system of two finite difference equations in three unknowns namely targets for GDP, inflation and nominal interest rates. The aggregate system's output is then observed under different policy scenarios subject to the same exogenous shocks.

A major criticism targeted at DSGE models is the way macro phenomena are generated. In these models, the output is either obtained by using a representative agent or aggregating over a set of homogeneous rational agents. However, studies in other disciplines have shown emergent macro phenomena having little or no relation to the individual agents' micro-behaviour. Schelling (1969) presents a clear example in the "social interaction paradox". This work demonstrates how the interaction of agents with only weak preferences for living in communities with similar agents results in extreme segregation often observed in the real world. A similar situation is observed by Reynolds (1987) in the "Birds in a flight paradox". Here, the systematic movement of a flock of birds is shown to emanate from the actions of individual bird interacting with other birds. Drawing from such case studies, several critics have noted that macro phenomena should also endogenously emerge from the dynamics of economic models in contrast to aggregated properties (Colander et al. 2009; Delli Gatti et al. 2010; Kirman 2010).

Another area where these models have come under severe criticism is the unrealistic assumption of extreme rationality. It is assumed that agents are endowed with infinite processing powers that enable them to ex-ante form rational expectations - requiring precise anticipation of the actions of other agents. The demands this assumption places on the agents is not only unrealistic but also time consuming. In fact, the very notion of agents rationally optimising a utility function has come under severe criticism since the emergence of behavioural economics (see Kahneman and Tversky 1984).

As the name suggest, DSGE models are simply stochastic flavours of neoclassical equilibrium models. As such, they suffer from the same limiting assumption of general equilibrium namely ”existence of fixed points”. In an equilibrium model, the market is always cleared by a price vector that is calculated by a fictitious ”Walrasian auctioneer” before transactions take place. However, the reverse is observed in real markets where the transactions and interactions of agents results in price formation (i.e. price is not a precondition). Moreover, it has been shown that general adjustment processes under which an economy returns to its original equilibrium state when perturbed may not necessarily exist (Ackerman 2002; Gaffeo et al. 2008). Similarly, Arthur (2006) has demonstrated the possibility of the occurrence of multiple equilibria, instability and chaos.

Although the aforementioned assumptions of rationality, representative agents and existence of equilibrium points facilitate tractability of a DSGE model. They, however, limit its use for modelling the emergence of unforeseen macro phenomena from interactions in an evolving complex system such as the occurrence of a financial crisis. Some critiques have even argued that the very notion of a crisis and the use of representative agents, equilibrium and assumption of rationality is by nature contradictory (Farmer and Foley 2009). Robert Solow succinctly summarises this in his remarks at the US Congress hearing ”...I do not think that the currently popular DSGE models pass the smell test. They take it for granted that the whole economy can be thought about as if it were a single, consistent person or dynasty carrying out a rationally designed, long-term plan, occasionally disturbed by unexpected shocks, but adapting to them in a rational, consistent way... The protagonists of this idea make a claim to respectability by asserting that it is founded on what we know about microeconomic behaviour, but I think that this claim is generally phony. The advocates no doubt believe what they say, but they seem to have stopped sniffing or to have lost their sense of smell altogether..." (Solow 2010).

3.2 Alternative Models

In the previous section, I showed that the top-down analytic approach employed in existing economic models requires over-simplified assumptions of rationality, representative agents and existence of equilibrium points which limits their use for designing regulatory policies. I overcome these limitations by employing agent based and network dynamics modelling techniques. An overview of these methods is provided in the following sections while specific implementation details are presented within the context subsequent chapters.

3.2.1 Agent based modelling

Agent based modelling facilitates the simulation of the economy as a complex evolving system. Agent based models belong to the class of Agent-based financial economics (ACE). ACE has emerged over the last two decades as a viable alternative for overcoming the limitations of existing economic models (see Fagiolo et al. 2007; Tesfatsion 2005, for a more detailed discussion on ACE). Agent based models are simply bottom-up frameworks that capture complex interactions of rationally bounded heterogeneous agents reacting and adapting to changing environmental condition in an evolving system lacking central coordination.

The complex interactions result in the emergence of unforeseen phenomena at the macro level such as a financial crisis rather than specifying such conditions ex-ante or simply aggregating over individual agents. Trichet (2010), for instance, advocates for agent based approaches as suitable alternatives to replace existing models in his remark that "The atomistic, optimising agents underlying existing models do not capture behaviour during a crisis period. We need to deal better with heterogeneity across agents and the interaction among those heterogeneous agents. We need to entertain alternative motivations for economic choices...Agent-based modelling dispenses with the optimisation assumption and allows for more complex interactions between agents. Such approaches are worthy of our attention". In the following paragraphs, I briefly distinct features characterising agent based frameworks that make them suitable for building economic and financial policy models:

First, agents can be separately endowed with different decision rules/heuristics in-order to facilitate heterogeneity. As such, agents are not necessarily pursuing the same objective. In fact, heterogeneity of the agents makes it possible to avoid the over simplifying assumption of representative agents in DSGE models. Moreover, agents are not endowed with super cognitive abilities that can enable them make decisions based on a complete knowledge of the entire complex system as assumed in a DSGE model. Rather, these decisions are heuristically driven from interactions in their local environments. In a sense, agents can only follow myopic optimisation rules as observed in the real world.

Furthermore, agents can adapt their behaviour to suit the demands of their constantly evolving environment. This by its very nature is at the heart of the evolution of the system resulting in a so-called "complex adaptive system". Due to constant behavioural adaptation, the evolving system of an agent based model can display macro-properties decoupled from individual behavioural characteristics. The ability to generate unforeseen emergent phenomena is one of the major strengths of an agent based model. For instance, the emergence of macro-patterns resulting from complex interactions of individual car drivers has been used by Geroliminis and Sun (2011) to explain the "phantom traffic jam" phenomenon.

Unlike their top-down DSGE counterparts, agent based models are built from blocks of individual agents incorporating realistic micro-foundations. The complex non-centrally coordinated interactions of these entities result in the emergence of macro-phenomena rather than them being imposed on the system ex-ante. Finally, the interactions in an agent based model can be non-linear as the system is not required to be mathematical tractable as in DSGE models. Hence, non-linearities in agents' interactions and in the feedback loops between macro and micro properties are easily captured in an agent based model.

The features identified in the preceding paragraphs make an agent based model an ideal tool for studying the causes and consequences financial crisis associated with systemic risk as well as designing effective mitigating economic and financial policies. The general framework for achieving such a task with an agent based model is briefly summarised below.

1. The process begins by defining the population set of agents required to address the policy question being investigated. For economic and financial policy questions, these agents would typically include firms, banks, households etc.

2. Agents are endowed with decision rules that enable them make heuristic choices given the limited information they obtain from their local environment. A finite number of micro/macro-economic variables and fixed parameters are used to characterize the behaviour of each agent.

3. Initial conditions are specified for each variable and parameter based on empirical observation of relevant real-world features.

4. The system is then allowed to evolve over a specified time period. The time steps are chosen to capture the time-scales of the real-world activity being modelled and can be in days, months, quarters, years etc. Each time step is seeded with the new environment variables resulting from the interactions in the previous time step.

5. The statistical properties of relevant emergent macro phenomena such as GDP, unemployment rate etc. are observed. These statistical properties are directly linked to the parameters used to initialise the system. Therefore, it is possible to think of agent based models as data generating processes of alternative worlds.

3.2.2 Network dynamics modelling

Financial institutions are intertwined due to dependencies arising from the asset and the liability side of their balance sheets. The 2007 financial crisis in which problems originating from the US subprime mortgage market rapidly spread to global financial markets revealed the significance of understanding the consequences of this interconnectedness (Crouhy et al. 2008). Fortunately, network modelling provides an intuitive way of representing and analysing these linkages between financial institutions. A network simply refers to a collection of points (nodes) paired together with lines (edges) (Newman 2010). Over the last years, many systems in varied fields have been represented and studied as networks including computer, social and biological networks. Consequently, an interdisciplinary field known as network theory has emerged that combines extensive set of scientific tools and techniques developed by drawing from such fields as physics, mathematics, statistics, biology etc.

In the context of financial systems; a network may be used to represent direct connections resulting from inter-institutional lending between financial institutions (e.g. interbank and repo transactions) or indirect connections due to similar asset investments such as linkages arising from overlapping portfolios. A node in a financial network will typically represent a financial institution or an asset while an edge may represent exposure to another institution in the case of direct connections or exposure to an asset in the case of indirect connections. Network theory provides a set of mathematical models such as random graphs, preferential-attachment, small world model for constructing patterns observed in real networks. This feature provides a convenient approach to study the implications of different network structures on the resilience of the financial system to external shocks as in (Albert et al. 2002; Allen and Gale 2000). Further, network theory also provides a set of tools for describing and analysing networks such as centrality measures and metrics. These techniques can be readily used in analysing static financial networks such as computing the degree centrality of financial institutions or checking for the present of hubs (i.e. highly connected institutions) in the systems. Finally, observed historical relationships tend to breakdown during a crisis. For instance, assets correlation and volatilities change in unanticipated ways in the event of a crisis. As such, it is mandatory for regulatory risk management models to be reactive and adaptable to changing environmental conditions. Network theory solves this challenge by providing theoretical frameworks for modelling the dynamics of a system as processes on networks such as percolation or epidemics on networks (Noh 2007). Leveraging on these frameworks makes it possible to design regulatory models that consider the vulnerability of the entire financial system to negative externalities such as the sudden failure of a bank or depreciation of an asset's value. Analysing a financial network generally involves initialising a model with nodes i.e. financial institutions and generating a network structure between the nodes empirically or theoretically. The network is then subjected to exogenous shocks which can involve shutting down one or more nodes (i.e. financial institutions) or perturbing the value of one or more assets and allowing the nodes react to these shocks subject to pre-specified regulatory constraints over a certain period. These processes are conceptualised in Figure 3.1. In Chapter 4, I provide a framework that concisely implements this approach.

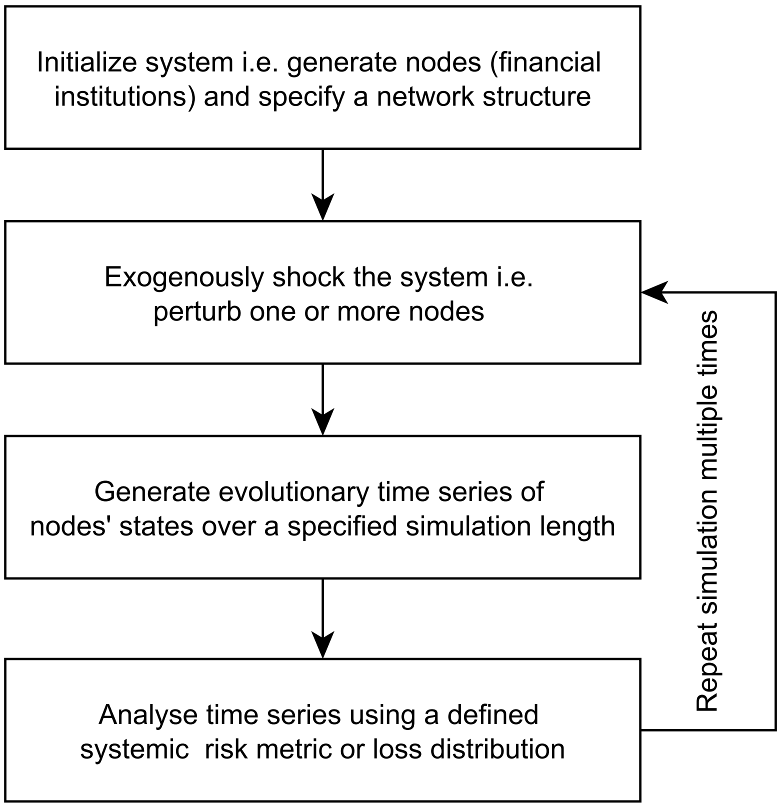


Figure 3.1: Analysing a financial network

Chapter 4

Overlapping portfolios

4.1 Introduction

Financial institutions are increasingly diversifying their balance sheet across several asset classes in-order to reduce the idiosyncratic component of their portfolio risk. This has led to increased global connectivity in the portfolio holdings across several institutions (Battiston et al. 2012b; Josselin Garnier et al. 2013). However, recent studies including (Arinaminpathy et al. 2012; Caccioli et al. 2011; Caccioli et al. 2014; Gai and Kapadia 2010; May and Arinaminpathy 2010; Nier et al. 2007) have shown that while increased interconnectivity can help diversify risk across the system, it also serves as a contagion propagating and amplification mechanism whenever a crisis is underway. This was partly the reason American International Group (AIG) was bailed out during the financial crisis as many of the biggest financial institutions had become exposed to it via derivative contracts (Scott 2012, provides more details). Financial institutions are connected directly via inter-institutional lending (e.g. interbank and repo transactions) and also indirectly through similar asset investments such as connections arising from overlapping portfolios. While the former has drawn the most attention from studies focusing on the role of counterparty and roll-over risks in propagating contagion (Arinaminpathy et al. 2012; Battiston et al. 2012a; Caccioli et al. 2011; Gai and Kapadia 2010; Gai et al. 2011; Iori et al. 2006; May and Arinaminpathy 2010), academics and policymakers have only recently begun paying close attention to the systemic risk posed by indirect connections associated with overlapping portfolios (Caccioli et al. 2014; Huang et al. 2013).

These connections provide a contagion channel for the propagation of mark-to-market portfolio losses to one or more financial institutions due to depression in asset prices resulting from fire sales by a distressed institution holding the same assets. In some cases, these losses may be sufficient to cause additional institutions to become distressed thereby resulting in more rounds of asset fire sales and further depression in asset prices. The 2007 quant crisis, for instance, was caused by a similar scenario in which the fire sales liquidation of the portfolio of one equity hedge fund depressed prices of assets held by other funds causing them to embark on additional rounds of selling which depressed asset prices even further and resulted in large portfolio losses (see Khandani and Lo 2007, for an elaborate discussion). The existing literature on overlapping portfolios have only considered bank interlinkages arising from a single asset class (Arinaminpathy et al. 2012; Cifuentes et al. 2005; Gai and Kapadia 2010; Nier et al. 2007). However, Caccioli et al. (2014) have recently generalised the fire sales model introduced in (Cifuentes et al. 2005) to the case of many assets. They characterised the stability of the financial system in terms of its structural properties including average degree, market crowding, leverage and market impact using a bipartite financial network model in which the contagion channel is formed through local portfolio overlaps between banks with homogeneous degrees.

However, their approach relies on the assumption of homogeneity in the degrees and sizes of all banks which may not necessarily be the case. In fact recent empirical studies (Braverman and Minca 2014; Guo et al. 2015; Iori et al. 2008; Marotta et al. 2015; Masi and Gallegati 2012) show that real financial networks of common portfolio holdings and balance sheet size distributions deviate from this assumption. Specifically, they provide evidence of a power law in these distributions. Following these findings, I generalise the approach in (Caccioli et al. 2014) to account for power law in the degrees and sizes of banks. I refer to banks with low degrees as specialised while those with high degrees are said to be diversified.

In this way, we can distinguish between the systemic risk contribution of different categories of banks ranging from very specialised to very diversified banks. Furthermore, I studied the effectiveness of various regulatory capital policy models guided by the intuition developed from the systemic risk contribution of the different types of banks. I then investigated the possibility of improving the system's stability by introducing structural correlation into the network without imposing new capital requirements. Finally, I characterise the stability response of the system with respect to leverage.

The model used for our simulations belongs to the same class of contagion mechanisms used extensively in the literature of counterparty network models (Gai and Kapadia 2010; Nier et al. 2007; Upper 2011). In a nutshell, the system is exogenously perturbed, and the resulting impact is recursively propagated through the network until no new default is observed. This feedback mechanism is essentially driven by asset devaluations based on a market impact function that revalues an asset with respect to its traded volume (Bouchaud and Cont 1998; Bouchaud et al. 2009). Our goal is to understand the impact of heterogeneity in the portfolio structure of banks on financial contagion due to overlapping portfolios. As such, I abstract from strategic processes used by banks in choosing a particular portfolio structure as in (Wagner 2011), who show using a micro-founded model that in equilibrium the risk of joint liquidation motivates investors towards heterogeneous portfolio configurations. Moreover, the mechanistic approach I consider keeps the model general enough for stress testing real financial systems by calibrating the model. I further assume passive portfolio management to keep the dynamics simple (i.e. banks do not deleverage or rebalance their portfolios during a crisis). In this sense, a bank's portfolio remains fixed until it becomes liquidated whenever it defaults. This assumption can be justified from the fact that most financial markets are illiquid relative to the positions held by large institutions such that whenever a crisis is underway, banks usually have insufficient time to deleverage until they become insolvent (see Caccioli et al. 2014, for an elaborate discussion).

Our stress tests reveal that heterogeneous bank degrees and sizes make the system more unstable relative to the homogeneous benchmark case with respect to random shocks but not with respect to targeted shocks. In contrast, heterogeneity in asset concentrations makes the system more resilient to random shocks but not with respect to targeted shocks. I then proceeded to study possible capital policy models guided by these results and find that a regulatory policy that assigns capital to the most specialised banks performs better than random assignments when the average degree is high. Moreover, diversification is a more significant factor than size in improving the financial system's resilience with capital based policies. The insights I develop can be used to address one of the major drawbacks of the Basel accords in ignoring the role of diversification for setting capital requirements (Committee of European Banking Supervisors 2010). An example is the risk weighted capital requirement framework which is heavily criticised for providing banks with incentives to concentrate in low risk asset classes such as interbank loans, sovereign debt etc. which not surprisingly turned out to be at the centre of the 2007 financial crisis (Wagner et al. 2012). Finally, I investigated the possibility of improving financial stability with a non-capital based policy that imposes a particular configuration in the bipartite network and find that disassortative mixing (i.e. connecting the most specialised banks with the most concentrated assets) increases the stability of the system.

The rest of this chapter is organised as follows. In the next section, I outline the main features of the model. In Section 4.3, I explore the stability impact of heterogeneous network topology and balance sheet sizes. Section 4.4 provides insights on the effectiveness of capital based policies and proposes a non-capital based policy by introducing structural correlations into the bipartite network. In Section 4.5, I study the impact of leverage on our model. Finally, a summary of our findings is presented in Section 4.6.

4.2 The Model

4.2.1 Network

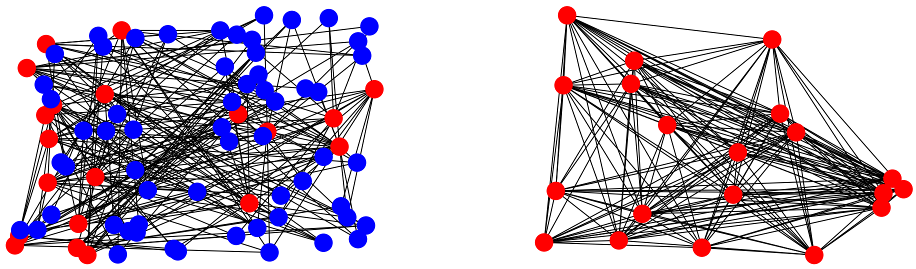
As in (Caccioli et al. 2014), I consider a bipartite network of a financial system consisting of N banks and M assets as shown in Figure 4.1. A link from bank i to asset j implies that j constitutes part of the portfolio of bank i. I define k_i as the degree (i.e. the total number of links) of bank i. Hence, the average bank degree is defined as:

$$\mu_b = \frac{1}{N}\sum_{i=1}^{N} k_i \tag{4.1}$$

Similarly, we can define the average degree of the assets as:

$$\mu_a = \frac{1}{M}\sum_{j=1}^{M} l_i \tag{4.2}$$

Where, l_j is the number of banks holding asset j in their portfolio. It is the case that the number of links emanating from both sides of the bipartite network must be equal i.e. $\mu_b N = \mu_a M$. Thus, I have that $\mu_b = \mu_a$ whenever $N = M$.



(a) Heterogeneous bipartite network (b) One-mode projection of banks

Figure 4.1: Left Panel: A Heterogeneous bipartite financial network. Banks are depicted in red circles while Assets are shown in blue. Right Panel: One-mode projection of the network to show indirect connections between banks.

4.2.2 Balance sheet structure

A typical bank's portfolio in the network discussed above consist of investments in non-liquid assets (e.g. shares in stocks) and liquid assets (e.g. cash). Figure 4.2 depicts the general structure of a bank's balance sheet. I have defined a bank's propor-

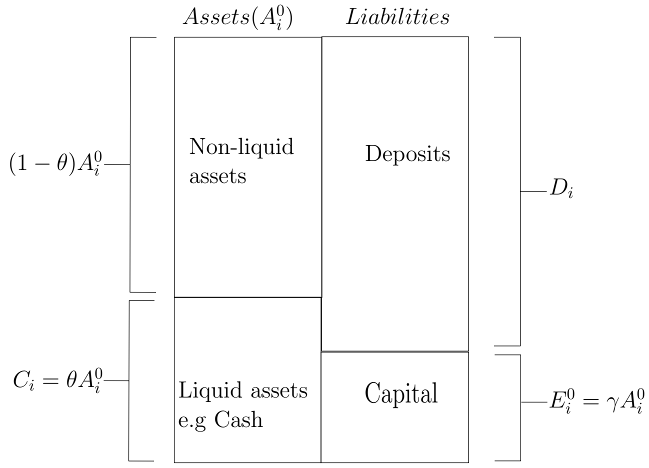


Figure 4.2: A typical bank's balance sheet structure. The bank holds a fixed amount of its asset in the form of cash, which value is assumed to remain fixed throughout the simulation for simplicity.

tion of liquid assets and initial capital as 20% and 4% of its total assets respectively for consistency with previous work (Caccioli et al. 2014; Gai and Kapadia 2010). Moreover, reports in (Upper 2011) suggest that the capital structure of banks in advanced economies typically conforms with this configuration. I define the total asset of bank i at any time t is defined as:

$$A_i^t = \sum_{j=1}^{M} Q_{ij} p_j^t + C_i \tag{4.3}$$

Where Q_{ij} denotes the number of shares of stock j held by bank i, p_j^t is the price of stock j at time t defined as:

$$p_j^t = p_j^{t-1} f_j(x_j^t) \tag{4.4}$$

Where x_j^t denotes the quantity of asset j sold at time t The capital (equity) of bank i at time t is given as:

$$E_i^t = A_i^t - D_i \tag{4.5}$$

In the model, a bank is declared insolvent whenever its initial capital endowment E_i^0 is completely eroded due to losses incurred from the depreciation of its asset values. Hence, I define the solvency condition for a bank i as:

$$A_i^0 - \sum_{j=1}^{M} Q_{ij} p_j^t - C_i \leq E_i^0 \tag{4.6}$$

We can also express the solvency condition for bank i as a condition on its initial leverage defined as $\lambda_i = A_i^0/E_i^0$ i.e.

$$\lambda_i \leq \frac{\sum_{j=1}^{M} Q_{ij} p_j^t + C_i}{E_i^0} + 1 \tag{4.7}$$

Hence, leverage is a necessary condition for a bank to fail since an unleveraged bank i.e. $(\lambda_i = 1)$ would always satisfy Equation 4.6.

4.2.3 Contagion mechanism

A typical simulation in our model follows the sequence enumerated below:

Step 1. Exogenously shock the system at time step $t = 0$

Step 2. Check banks for solvency condition as in Equation 4.7 at each successive time steps $t = 1, 2, ..$

Step 3. Liquidate the portfolios of any newly bankrupt banks and re-compute asset prices [1]

Step 4. Terminate the simulation when no new default(s) occurs between successive time steps.

This dynamics is captured by the flowchart depicted in Figure 4.3

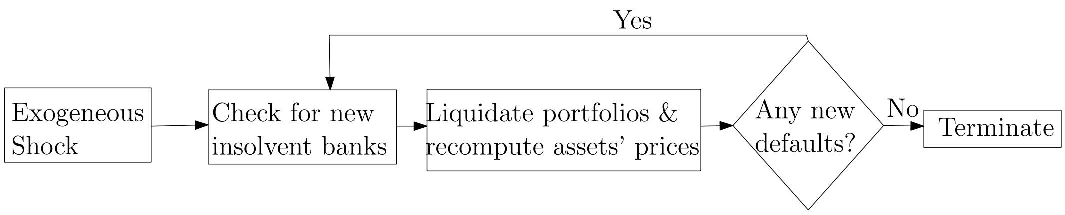


Figure 4.3: Flowchart representation of the contagion mechanism. A Bank is only declared bankrupt whenever it becomes insolvent.

4.2.3.1 Exogenous shocks

I consider two kinds of initial shocks: random and targeted shocks. In a random shock, a bank or asset is randomly selected and exogenously perturbed while a specific kind of bank or asset is perturbed in the case of a targeted shock.

[1] In order to keep the model simple, I assume that the liquidated assets are traded with parties outside the banking system.

4.2.3.2 Market impact

I assume a market impact function of the form $f_j(x_j) = e^{-\alpha x_j}$ as in (Arinaminpathy et al. 2012; Cifuentes et al. 2005; Gai and Kapadia 2010) such that x_j is the liquidated fraction of asset j. The price of asset j is then updated according to the rule: $p_j \to p_j f_j(x_j)$. As in (Caccioli et al. 2014; Gai and Kapadia 2010; Nier et al. 2007), I set $\alpha = 1.0536$ such that the liquidation of 10% of an asset results in a 10% price drop in the asset's value.

4.2.3.3 Systemic stability

I characterise the stability of the financial system in terms of the systemic risk posed by an exogenous shock. I define systemic risk as the probability that contagion occurs. In the context of our model, contagion is said to occur only when the number of cascading defaults resulting from an exogenous shock exceeds a critical threshold ϕ. I define ϕ as 5% of the total number of banks in the system for consistency with previous work on financial contagion (Caccioli et al. 2014; Gai and Kapadia 2010).

4.3 Stability Analysis

The existing literature on financial contagion due to overlapping portfolios have only considered banks with homogeneous (i.e. similar) degrees and sizes (see Caccioli et al. 2014; Cifuentes et al. 2005), for instance, (Caccioli et al. 2014) consider a homogeneous financial network using an Erdős-Rényi bipartite networks. However recent empirical studies by (Braverman and Minca 2014; Guo et al. 2015; Marotta et al. 2015; Masi and Gallegati 2012) have shown that real portfolio networks are far removed from such distributions. In particular, they show the existence of a power law in the degree distributions in a network of overlapping portfolios similar to the observations reported in (Boss et al. 2004; Caccioli et al. 2015) for counterparty networks.

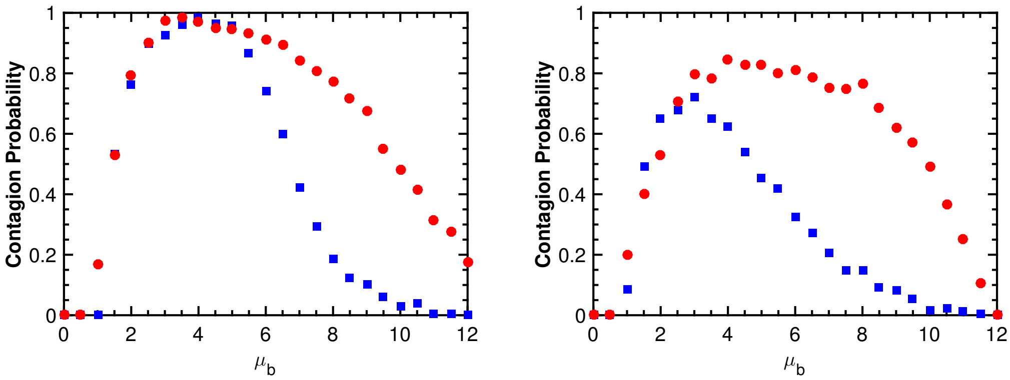
4.3.1 Heterogeneous bank degrees

In this chapter, I investigate the stability impact of heterogeneity in the degree of banks. As such, I consider a heterogeneous bipartite financial networks where the degrees of banks are generated according to a power law distribution i.e. $P(k) \propto k^{-\gamma}$

with $\gamma = 2.5$. Each bank then forms a link with a random asset until it reaches its generated degree such that no bank is linked to an asset more than once. This link formation approach implies that the number of links of the assets follows a Poisson distribution since every asset has the same probability of being selected. A bank's degree can be interpreted as its level of diversification since it denotes the number of different investments of the bank. I have used the term *specialised bank* to mean a bank with focused investments in contrast to a bank holding a diversified portfolio. Our focus here lies in understanding the systemic risk contribution of different types of banks ranging from very specialised to very diversified banks without mixing in the influence of size. This approach mandates an assumption of the same balance sheet sizes across all banks.

In the left panel of Figure 4.4, I plot the probability of contagion as a function of μ_b when a random bank fails. I compare the unstable region for the system with heterogeneous bank degrees relative to the homogeneous case. We find that the unstable region is wider in the heterogeneous system. The right panel of Figure 4.4 shows that this observation is independent of the kind of exogenous shock. In particular, I plot the contagion probability for the case when an asset is randomly devalued and still find that heterogeneity in banks' degree results in greater instability. The existence of a wider unstable region in the heterogeneous system can be understood by observing that contrary to the homogeneous case, the heterogeneous system is characterized by a few highly diversified banks and many specialized banks. Hence, the probability that a specialized bank is hit from the initial shock is relatively higher. Consequently, specialised banks induce higher devaluations on their assets since they hold large amounts of these assets.

However, this result contrasts with general reports in the complex networks literature in which heterogeneous network topology has been shown to create more stability, for instance, Caccioli et al. (2011) show that heterogeneity in a counterparty network creates a more robust system relative to the homogeneous case. The reason for this lies in the fact these previous works have considered a network of direct bilateral exposures between the heterogeneous agents such that the few hubs



(a) Bank shock (b) Asset shock

Figure 4.4: Left Panel: Contagion probability as a function of μ_b for the case when a random bank fails. Red circles: system with heterogeneous bank degrees. Blue squares: system with homogeneous bank degrees. Right Panel: Contagion probability as a function of μ_b for the case when a random asset is devalued. Contagion is worse in the heterogeneous system irrespective of the kind of exogenous shock. Result refer to 1000 simulations for $N = M = 1000$

(i.e. the most connected) nodes become the most systemically relevant whereas the specialised nodes are the most systemically relevant in this case since they concentrate their investments in specific assets and thereby carry higher liquidation risk. This result sheds some light to why specialised institutions like mortgage banks, building and loan associations, specialist funds etc. who hold significant amounts of specific assets should be considered systemically important as the fire sales of these assets conditional on their default may have devastating impacts on asset prices. Moreover, this finding provides further credence to the conjecture given by Andrew Haldane, the Bank of England's Chief Economist, in one his speeches that the "rapid growth in specialist funds potentially carry risk implications, both for end-investors and for the financial system as a whole" (Haldane 2014). Furthermore, Wagner (2011) also suggests imposing higher diversity requirements on portfolio holdings of financial institutions with high liquidation risk relative to those with low risk.

In Figure 4.5, I show the impact of targeted shocks on the stability of the system. I plot the probability of contagion as a function of μ_b when the initial shock is aimed at specific banks. We find that the unstable region is widest when any of the top 5% most specialised banks is hit while targeted shocks on any of the top 5% diversified banks results in the smallest unstable region. This can be understood from the fact that banks hold lesser amounts of specific assets with increasing degrees since I assume here that all banks are endowed with the same asset sizes. Hence, targeting shocks at the most diversified banks would effectively close the fire-sale contagion channel quicker since only small amounts of assets would be sold, which implies lower price devaluation than the case when banks are randomly perturbed. However, the reverse is observed when shocks are directed at the most specialised banks since they hold significant amounts of specific assets and thereby carry higher liquidation risk. I refer to these banks as ”Too Specialised To Fail” (TSTF).

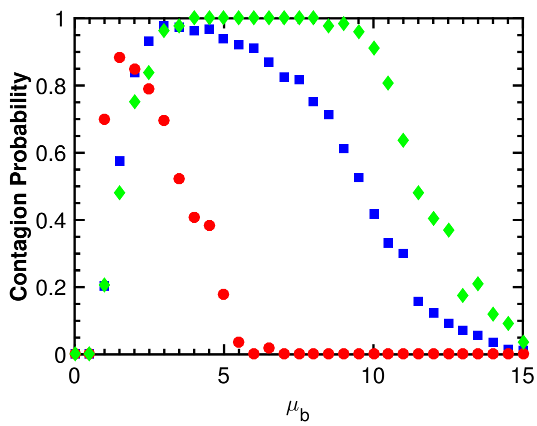
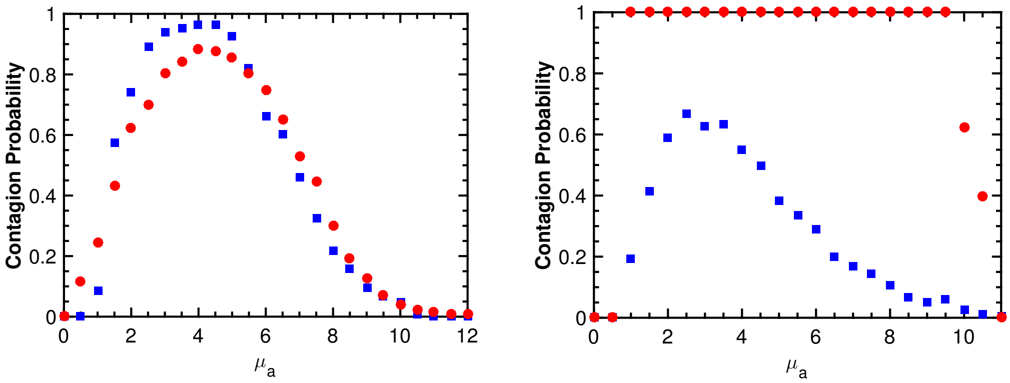


Figure 4.5: Contagion probability as a function of μ_b when banks have heterogeneous degrees. Blue squares: contagion probability when a random bank fails. Green diamonds: contagion probability when shocks are targeted at the most specialised banks. Red circles: contagion probability when shocks are targeted at only the most diversified banks. The region where contagion occurs is widest when specialised banks are targeted. Result refer to 1000 simulations for $N = M = 1000$

4.3.2 Heterogeneous asset concentration

In the previous section, I introduced heterogeneity into the distribution of the banks' degrees and the number of banks holding each asset is homogeneous. In this section, I turn our attention to the case when the distribution of the number of banks holding each asset class is heterogeneous and the degree distribution of banks is homogeneous. I follow the approach of the previous section and assume a power law distribution in the asset concentrations. An asset's concentration can be interpreted as the preference of banks towards that asset class. Our aim is to study how this preference structure affects the stability of the entire system.



(a) Random shocks (b) Targeted shocks

Figure 4.6: Left Panel: Contagion probability as a function of μ_a for homogeneous and heterogeneous distributions of asset concentrations. Blue squares: system with homogeneous asset concentrations. Red circles: system with heterogeneous asset concentrations. A random bank fails in both cases. Introducing heterogeneity into the distribution of asset concentrations results in a more robust system. Right Panel: Targeted shocks on a system with heterogeneous asset concentrations. Targeting concentrated assets amplifies contagion probability. Result refer to 1000 simulations for $N = M = 1000$

In the left panel of Figure 4.6, I plot the probability of contagion as a function of average asset concentration for the case when a random bank fails. In contrast to the results observed for heterogeneous bank degrees, we find that introducing heterogeneity in the concentration of the assets produces a more robust system relative to the homogeneous system. This can be understood from the fact that the probability than a highly concentrated asset is perturbed is relatively low since the scale free network comprises very few concentrated assets and many less concentrated (i.e. isolated) ones. This effectively reduces the unstable region since fewer banks are affected by contagion.

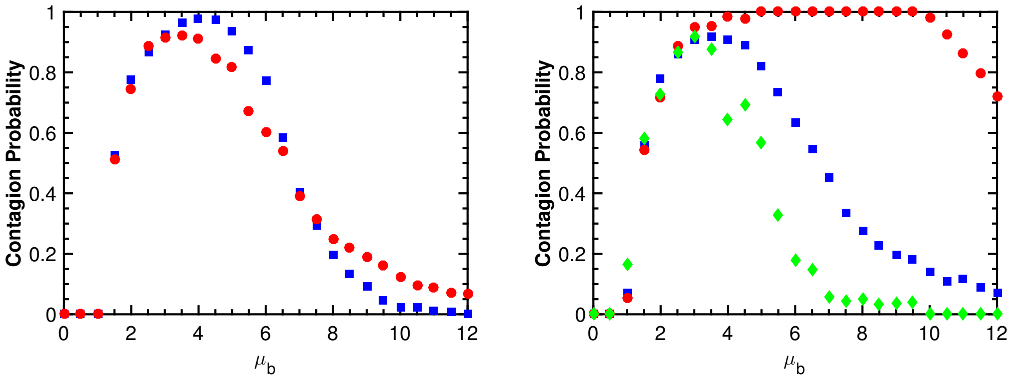
The right panel of Figure 4.6 shows the stability impact of aiming initial shocks at any of the top 5% most concentrated assets. As expected, targeting initial shocks at these highly concentrated assets has the effect of amplifying contagion since more banks' portfolios are negatively affected by the initial asset devaluation. However, the width of the unstable region is essentially the same as in the homogeneous system. This is so because as soon as banks reach a critical average degree they become resilient to contagion irrespective of the kind of shock on the asset side.

4.3.3 Heterogeneous bank sizes

In the previous sections, I assumed that all banks have the same balance sheet sizes in order to separate the influence of size from diversification. However, empirical evidence in the literature clearly suggest that banks also have largely heterogeneous sizes (Boss et al. 2004). For instance, a recent data analysis by SNL Financial shows that the top 5 biggest banks have 44% of the total assets held by banks in the U.S. (Schaefer 2014). Our aim in this section is to study the impact of this kind of heterogeneity in the size distribution of banks on the stability of the financial system. To do this, I model the bank sizes according to a power law distribution i.e. $P(A) \propto A^{-\gamma}$ resulting in the creation of a few banks with significantly larger asset sizes than most banks whilst abstracting from the influence of diversification by assuming a Poisson degree distribution.

In the left panel of Figure 4.8, I plot the probability of contagion as a function of μ_b for the case of random bank shocks. We find that contagion halts much faster when banks have homogeneous sizes relative to the heterogeneous case. The following argument provides an intuition to why this is the case. In the heterogeneous system, the fire sales impact on asset prices is more severe whenever any of the large banks are hit as these banks hold significant amounts of their assets relative to the entire system since I have assumed a Poisson degree distribution. This effectively shifts the critical threshold for which contagion is no longer possible to the right.

The right panel shows the contagion probability as a function of μ_b for the case of initial shocks to specific banks. We observe that the system is significantly more



(a) Random shocks (b) Targeted shocks

Figure 4.7: Left Panel: contagion probability as a function of μ_b for homogeneous and heterogeneous distribution of banks' sizes. Blue squares: system with similar balance sheet sizes. Red circles: system with heterogeneous balance sheet sizes. The system is subject to random bank failures in both cases. Contagion probability is wider in the heterogeneous system relative to the homogeneous case. Right Panel: Targeted shocks on a system with heterogeneous distribution of banks' balance sheet sizes. Blue squares: contagion probability when a random bank is perturbed. Red circles: contagion probability when shocks are targeted at the biggest banks. Green diamonds: contagion probability when shocks are targeted at the smallest banks. Targeting shocks at the biggest bank results in the widest unstable region. Result refer to 1000 simulations for $N = M = 1000$.

unstable when exogenous shocks are targeted at any of the top 5% biggest banks but more stable when the shocks are targeted at any of the top 5% smallest banks. This follows from the fact that big banks hold larger amounts assets for each value of μ_b relative to other banks, which implies that targeting shocks at them would cause higher devaluations of the asset classes they hold, effectively fuelling the contagion mechanism that leads to a wider unstable region. I refer to these banks as ”Too Big To Fail” (TBTF).

In summary, the findings of the stress tests conducted in Section 4.3 are the following:

(i) Introducing heterogeneity in the degrees of banks exacerbates the fragility of the system to random shocks in contrast to (Caccioli et al. 2011; Gai and Kapadia 2010) who show that a scalefree counterparty network results in a more robust system with respect to random shocks. We find that this result is independent of the type of exogenous shock (i.e. bank or asset shock). Furthermore, we find that targeting the most specialised banks makes the system more unstable.

(ii) Heterogeneity in asset concentrations improves the resilience of the system to random shocks in contrast to heterogeneous bank degrees. Moreover, targeting highly concentrated assets increases the probability of contagion, however the average degree threshold where contagion dies out is effectively unchanged.

(iii) Cascading default is halted slightly faster when banks have homogeneous sizes relative to the heterogeneous case and is greater when exogenous shocks are targeted at the biggest banks.

4.4 Policy Impact Analysis

The 2007-2009 financial crisis has precipitated calls for higher regulatory capital requirements for banks. Although higher capital requirements can improve financial stability, they however carry some implicit costs [2] namely reduced profitability for banks and higher lending cost which may have a negative impact on social welfare (Bridges et al. 2014; Brooke et al. 2015; IMF 2016). Hence, it is important that new regulatory capital requirements are assigned to banks in the way that gives the most stable configuration. To this end, I investigate how the intuition developed from the stress tests in Section 4.3 can influence capital based regulatory policies. I then propose an alternative non-capital based policy by studying the structure of the bipartite network.

4.4.1 Capital based policy

Here, I compare the performance of possible capital policy models following the intuition developed in Section 4.3. In each model, the same amount of capital χ is injected into the system. The difference in the policies lies in the way χ is distributed amongst the banks.

4.4.1.1 Targeted versus random

The stress tests done in Section 4.3 suggests that the ”Too Specialised To Fail” and ”Too Big To Fail” banks are systemically important. Hence, it becomes interesting to ask if assigning capital requirements to only this group of banks can improve financial stability relative to targeting a random group of banks. I consider two kinds of targeted policies. In one, I assign the capital equally to only the top 5% most specialised banks and refer to this policy as T_S while in the second, which I call T_B, only the top 5% biggest banks are required to hold more capital. I model a random policy for comparison. In the random policy, 5% of the banks are randomly selected and assigned additional capital requirements equally.

T_S : I now investigate the stability impact of the T_S policy relative to the random policy as such I abstract away from the influence of size by assuming similar balance sheet sizes across all banks. I show this comparison in left panel of Figure 4.8 by

[2] This is based on the assumption that Modigliani-Miller theorem does not hold, which essentially implies that a bank's capital structure does not affect profit or social welfare in an idealised world without frictions such as interest payments on debts, taxes, bankruptcy and agency costs (Franco Modigliani 1958).

computing the ratio R of the contagion probability of both policies as a function of μ_b such that $R = 1$ implies similar performance, $R > 1$ means the T_S policy supersedes the random policy and $R < 1$ implies that the random policy outperforms the T_S policy. I focus our analysis on only those regions where contagion occurs in both systems to avoid divisions by zero. The plot suggests that a policy that focuses on the most specialised banks results in greater stability relative to a random policy in the region with high values of μ_b, which is significant from a policy perspective because real world financial networks are more likely to be in this region.

The right panel of Figure 4.8 provides an insight to why the T_S policy outperforms the random policy. It shows the probability that a bank i with degree k_i defaults before the occurrence of contagion. The plot suggest that the specialised banks are the most likely to default before contagion occurs. As such, it is reasonable to conjecture that focusing the capital policy on these banks is more likely to increase the resilience of the system.

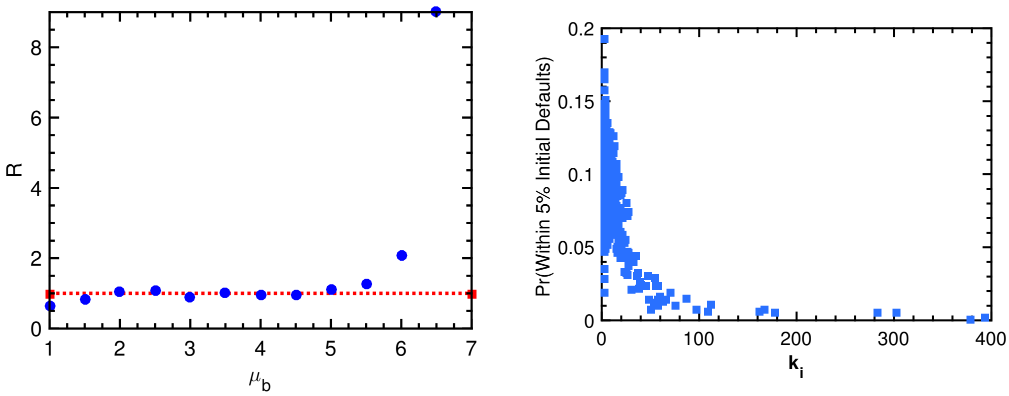


Figure 4.8: Left panel: Stability impact of T_S policy relative to the random policy for a system with heterogeneous bank degrees. Dotted line: comparison basis i.e. R=1. The T_S policy produces more stability relative to the random policy for high values of μ_b. Right panel: Probability that a bank i with degree μ_i defaults before contagion occurs. The most specialised banks have a greater chance of defaulting before contagion occurs.

T_B : I now abstract from heterogeneous degrees and consider only heterogeneous sizes in-order to study the stability impact of the T_B policy relative to the random policy. I show this comparison in left panel of Figure 4.9 by computing the ratio R of the contagion probability of both policies as a function of μ_b such that $R = 1$ implies similar performance, $R > 1$ means the T_B policy supersedes the random policy and $R < 1$ implies that the random policy outperforms the T_B policy. The plot markers oscillate around 1 suggesting that a policy that focuses only on the biggest banks is not effective.

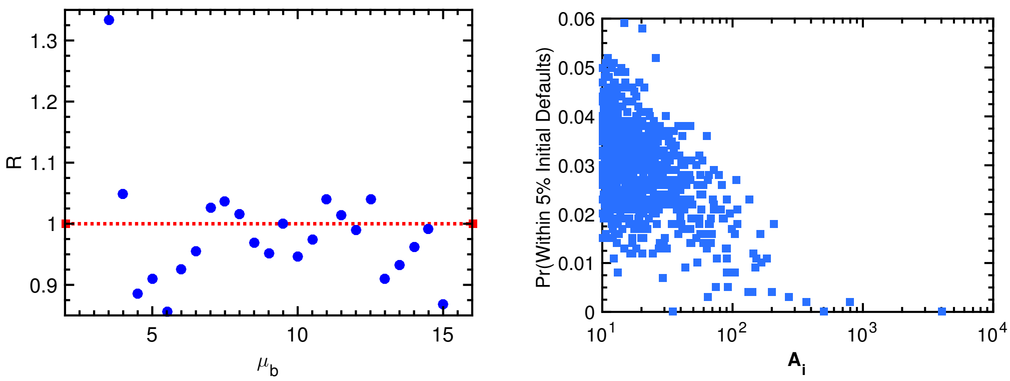


Figure 4.9: Left panel: Stability impact of T_B policy relative to the random policy for a system with heterogeneous bank sizes. Dotted line: comparison basis i.e. $R = 1$. The T_B policy appears to be ineffective relative to the random policy. Right panel: Probability that a bank i with size A_i (shown in log scale) defaults before contagion occurs. The biggest banks have a greater chance of defaulting before the occurrence of contagion.

In order to understand why the T_B policy does not perform better than the random policy, I plot the probability that a bank i with size A_i defaults before the occurrence of contagion in the right panel of Figure 4.9 and find that big banks have a smaller chance of failing before contagion occurs. This implies that allocating capital requirements to only these banks is likely to be ineffective in the context of this model.

4.4.1.2 Diversification versus size

In the previous section, I simplified the model in-order to separate the impact of diversification and size. However, it is also interesting to ask which of the two factors namely diversification and size is the more significant factor for capital requirement policies. In-order to facilitate this comparison, I introduce heterogeneity into the degrees and sizes of the banks. The diversification-based policy I consider assigns capital requirements to banks based on their degrees such that banks with higher degrees are required to hold lesser capital i.e.

$$\varepsilon_i = \frac{1/k_i}{\sum_i 1/k_i}\chi \tag{4.8}$$

Where, k_i denotes the degree of bank i. While the size-based policy allocates capital requirements to banks based on the size of their balance sheets such that big banks are required to hold more capital i.e.

$$\varepsilon_i = \frac{A_i}{\sum_i A_i}\chi \tag{4.9}$$

Where, A_i denotes the size of bank i. In Figure 4.10, I compare the stability impact of a diversification based policy relative to a size based policy by computing the ratio R of their respective contagion probabilities as a function of μ_b such that $R = 1$ implies similar performance, $R > 1$ means the diversification based policy supersedes the size based policy and $R < 1$ implies that the size based policy outperforms the diversification based policy. The figure suggests that assigning capital based on a bank's degree supersedes assignment based on size further confirming recent findings reported by Cai et al. (2012).

4.4.2 Non-capital based policy

From a policy maker's perspective, it is interesting to ask if there is a network structure that improves systemic stability without imposing new capital requirements (see Thurner and Poledna 2013, for example)? I address this question by introducing some structural correlation into the bipartite network. In the subsequent paragraphs, I use the term "assortative network" for a bipartite network in which the most diversified banks hold the most widely held (i.e. concentrated) assets and "disassortative network" for one in which the most specialised banks hold the most widely held assets while the most diversified banks hold the least held assets. The correlated networks are generated based on the algorithm proposed in Noh (2007). The procedure essentially involves minimising a network cost function until a sta-

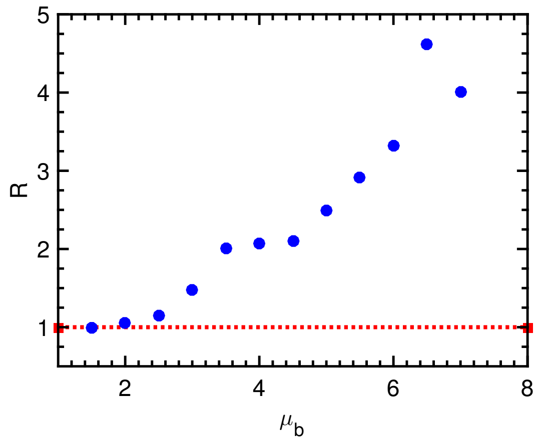


Figure 4.10: Stability impact of policy based on diversification relative to policy based on size as a function of μ_b for a system with heterogeneous sizes and degrees. Using banks' diversification levels as a proxy for assigning capital requirements is superior to using bank sizes.

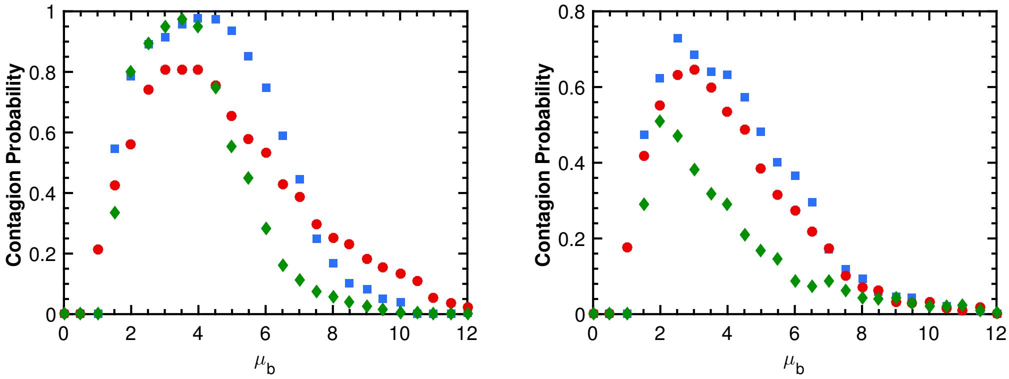
tionary state using Monte Carlos simulations. This cost function is defined as:

$$H(G) = -\frac{J}{2}\sum_{i,j=1}^{N} a_{ij}k_ik_j \tag{4.10}$$

$$a_{ij}\begin{cases} 0, & \text{if } i = j \\ 1, & \text{otherwise} \end{cases}$$

Where, $k_i = \sum_j a_{ij}$ and J denotes a control parameter for tuning the level of assortativity i.e. $J < 0 (J > 0)$ gives a disassortative (assortative) network respectively while $J = 0$ produces an uncorrelated network.

In the left panel of Figure 4.11, I study the resilience of the system as a function of μ_b for the different network configurations for the case when a random bank fails. The right panel shows the same plot but for the case when a random asset is devalued. In both cases, we find that the disassortative network produces the most stable configuration. This is so because in a disassortative network, assets with high concentration are held by the most fragile banks (i.e. banks with low degrees). This implies that fire sales impact on the asset prices resulting from the default of any of these fragile banks would be minimal. However, in the assortative network, assets with low concentration degrees are held by these fragile banks, which implies that



(a) Bank shock (b) Asset shock

Figure 4.11: Left Panel: Contagion probability as a function of μ_b for different network correlation configurations subject to the initial failure of a random bank. Blue squares: Uncorrelated network. Red circles: Assortative network. Green diamonds: disassortative network. The disassortative network gives the most stable configuration, while the assortative network results in the most unstable system. Right Panel: Contagion probability as a function of μ_b for different network correlation configurations. Again, the disassortative network gives the most stable configuration.

the fire sales resulting from their default would be much more severe thus leading to a wider unstable region. This result raises a question of whether it is possible to implement a structure of incentives that makes the bipartite network disassortative?

4.5 Impact of Leverage

I now study the joint role of leverage (i.e. λ) and average degree (i.e. μ_b) on the stability of our heterogeneous system. In Figure 4.12, I show that the existence of the critical leverage threshold for which contagion occurs with non-zero probability reported by Caccioli et al. (2014) for a homogeneous system is preserved when banks have heterogeneous degrees for each μ_b and that this threshold is increasing with μ_b irrespective of other prevailing conditions. This suggests that it may be possible for a financial regulator to permit higher leverage in the system by promoting an appropriate diversification strategy that achieves a particular value of μ_b which may not be individually optimal for the banks similar to the findings reported in (Beale et al. 2011; Tasca et al. 2014).

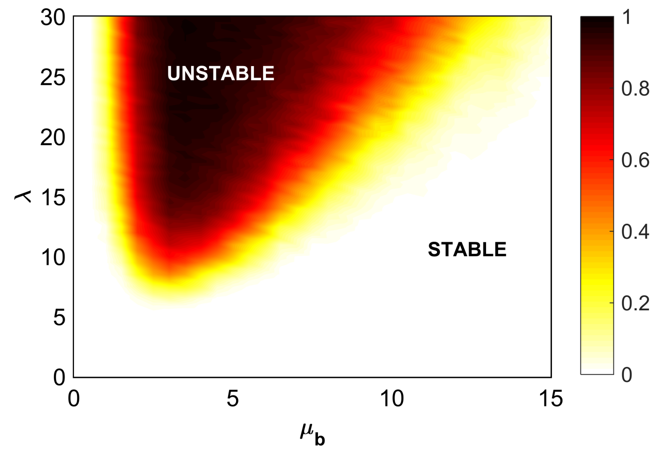


Figure 4.12: The non-white region refers to parameter values of λ and μ_b that result in non-zero contagion probability. There is a critical leverage value below which the system is stable for any value of μ_b.

4.6 Conclusion

Previous studies on overlapping portfolios have relied on the assumption of homogeneity in the degrees and sizes of banks, however, empirical findings show that real financial networks deviate from this assumption (Boss et al. 2004; Braverman and Minca 2014; Guo et al. 2015; Marotta et al. 2015; Masi and Gallegati 2012). In particular, they provide evidence that bank degrees and sizes follow power law distributions. In our work, I generalised the model recently introduced in (Caccioli et al. 2014) to account for these features. This approach makes it possible to study the systemic risk contribution of different types of banks with varying degrees and sizes. I found that separately introducing heterogeneity into the degrees and sizes of the banks widen the unstable region relative to the homogeneous case with respect to the initial failure of a random bank but not with respect to targeted shocks. In contrast, heterogeneity in asset concentrations makes the system more resilient to random shocks but not with respect to targeted shocks.

Based on these intuitions, I proceeded to study possible capital policy models. Our findings suggest that a regulatory capital policy that assigns capital requirements to the most specialised banks performs better than random capital assignments when the network connectivity is high. However, focusing capital requirements on only the biggest bank does not appear to be effective relative to random assignments within the context of our model. Furthermore, I investigated the relevance of using diversification or size in building the capital based policies and find that the diversification-based policy outperforms the size based policy with increasing network connectivity.

I then proposed a non-capital based policy that improves financial stability by introducing structural correlation into the bipartite network. Our results suggest that disassortative mixing (i.e. connecting the most specialised banks with the most concentrated assets) improves the resilience of the system. This can be understood from the fact that the fire sales impact of the specialised banks is significantly reduced due to the smaller quantity of traded shares relative to the entire volume of the assets. Finally, I studied the joint role of leverage and average degree on the stability of our heterogeneous system and found that the existence of a critical leverage beyond which contagion occurs with non-zero probability for each average degree reported in (Caccioli et al. 2014) for a homogeneous system is preserved when banks have heterogeneous degree distribution. This finding further reinforces calls for policy makers to compensate for higher system risk induced by higher leverage by promoting an appropriate diversification strategy.

In the next chapter, I break away from the mechanistic stress test models used in this chapter and consider a more realistic agent based model in which the systemic risk from overlapping portfolios is endogenously created. This way I can implement measures to disincentive banks from structuring their portfolios in a manner that increases the fragility of the system.

Chapter 5

Diversification

5.1 Introduction

There is growing similarity in the asset side of banks' balance sheets due to increased participation in the same global markets (Cai et al. 2012; Liu 2015; Wagner 2010). I consider the consequences of this on financial stability. A major motivation for the increasing similarity is rooted in the standard financial and perhaps intuitive diversification advice "Don't put all your eggs in one basket". In fact, the seminal work of Markowitz (1952) on portfolio selection provides evidence that diversification across various asset classes reduces the aggregate risk of a bank's portfolio. It is thus reasonable to conclude that if each bank becomes less risky due to diversification then the financial system should become more stable. Moreover, several reports before the 2007 financial crisis found little evidence for a systemic breakdown of the financial system owing to the high diversification levels at individual banks due to the extent of financial innovation (Bartram et al. 2007; Elsinger et al. 2006; Furfine 2003). However, the financial system still came close to near collapse even though banks, especially the big ones, had become largely diversified.

This conundrum stems from an individual bank not considering the fact that other banks are pursuing the same risk objective by diversifying their balance sheets across the same set of asset classes. This results in individual banks becoming less differentiable. From a systemic perspective, a less differentiable set of banks increases fragility and exacerbates the risk of joint failures of a large part of the financial system, which can have serious consequences on social welfare. This phenomenon draws a parallel in ecological studies where genetic diversity, for instance, is shown to result in greater resilience to disease spread (see Tilman 1999, for a detailed discussion).

Thus, diversification appears to serve multiple roles; on one hand, it makes banks less risky but on the other hand it increases the risk of joint failures. This dual role of diversification on financial stability has prompted active discussions amongst policy makers and academics in a growing number of studies. For instance, the reports by (Allen and Carletti 2006; Allen and Gale 2005; Wagner 2008; Wagner 2010; Wagner and Marsh 2006) show that diversification increases the likelihood of a systemic crisis due to the homogenization of the financial system even though it is desirable in terms of reducing the probability of an individual bank failure. Similar findings are reported by Battiston et al. (2012b). In a related work, Caccioli et al. (2014) study the role of diversification on financial contagion due to overlapping portfolios and showed that the system undergoes two phase transitions with increasing diversification between which global cascades can occur. This finding is also reported in the work by Raffestin (2014). Tasca et al. (2014) show that diversification can have ambiguous consequences on the stability of the financial system by studying the joint impact of leverage and diversification on financial stability using a structural risk model based on the framework proposed by Merton (1974). They show that a critical leverage value can result in alternating phases of stability and instability depending on the diversification strategy. Finally, while our focus is on diversification, however our work is also related to the literature on bank herding since they both lead to concentrations in the same set of activities (see, for instance, Acharya and Yorulmazer 2005; Acharya and Yorulmazer 2007).

I contribute to this strand of literature by studying the consequences of diversification on the stability of the financial system in terms of idiosyncratic and systemic risk endogenously produced from an evolving stylised economy, which sets our work apart from previous studies. Moreover, our approach provides a simple mechanism for analysing the full effect of regulatory responses to negative externalities associated with the impact of diversification on financial stability and the wider economy.

Our approach consists of a deliberately simplified agent based model that couples a financial system and the real economy. There is a large literature on macro-finance interaction models including (Bask 2012; De Grauwe and Macchiarelli 2015; Lengnick and Wohltmann 2016; Naimzada and Pireddu 2014; Westerhoff 2012). These works couple agent-based financial(stock) market and mainstream macro models. However, I deviate from these models by focusing on externalities resulting from credit/loan network rather than traded equities/shares [1]. In a nutshell, the model implements a self-organising economy populated by rationally bounded heterogeneous agents including firms, households and banks interacting within different markets without central coordination (see Fagiolo and Roventini 2012, for an elaborate discussion on decentralised economic systems). The model dynamics leads to the emergence of bank-bank and bank-firm links that are strategically formed and terminated. These networks serve as channels of contagion and shock propagation. In this sense, the model shares some similarity with the strand of literature on multilayer network theory and financial contagion (Caccioli et al. 2015; Kok 2013; Lux 2016; Martinez-Jaramillo et al. 2014; Poledna et al. 2015) since it leads to the formation of different network structures that serve as contagion reinforcing mechanisms.

Although, I only consider diversification in the loan portfolio of banks as the cause for increased similarity amongst banks. However, other reasons for increased similarity across financial institutions have been identified in the literature on bank herding such as the increasing adoption of standardised and “best practise” risk management and trading strategies across financial institutions that causes them to respond to market conditions in the same way (Farrell and Saloner 1985). For instance, the 2007 quant meltdown event, during which several large quantitative long-short equity hedge funds experienced massive losses resulting from following

[1]This is motivated by the fact that empirical reports published in 2007 for banks in the United Kingdom, for instance, suggest that on average 80% of a bank’s balance sheet represented loans given to firms while only about 10% was allocated to equities (see Anand et al. 2013)

the same trading strategy that encouraged multiple rounds of asset liquidation after one or more funds rapidly liquidated a large chunk of their portfolio. This situation caused prices to spiral downwards and eventually led to large portfolio losses across the system (see Khandani and Lo 2007, for an elaborate discussion on this event). Acharya and Yorulmazer 2005; Acharya and Yorulmazer 2007 further suggest higher probability of being bailed out in the event of joint failures as another reason why banks undertake similar activities.

The rest of this chapter is organised as follows. In Section 5.2, I describe the main features of the model. Section 5.4 characterises the stability features of the financial system due to diversification. I then propose a regulatory policy that permits diversification without exacerbating systemic risk in Section 5.5. Finally, a summary of our findings is presented in Section 5.6.

5.2 Model

For the purpose of this study, I extend the CRISIS Mark 1 agent based model extensively studied in (Delli Gatti et al. 2011; Gualdi et al. 2015; Klimek et al. 2015; Poledna and Thurner 2016). The original CRISIS Mark 1 model specifies a stock-flow consistent system that couples the real economy and a limited financial system. I extend the model to include different production sectors in the real economy. Furthermore, I include simplified credit and interbank markets so that banks play an active role in the economy unlike the original model specification in which the banking sector is passive.

Figure 5.1 provides a high-level view of the agents and their interactions within the model discussed elaborately in the following sections: In a nutshell, the model implements a self-organising economy populated by rationally bounded heterogeneous agents including firms, households and banks interacting within different markets without central coordination. Households interact with firms on the labour and consumption market, banks interact with other banks on the interbank market while firms and banks interact within different sectors on the credit market resulting in a constantly evolving (i.e. links are strategically formed and terminated) bank-

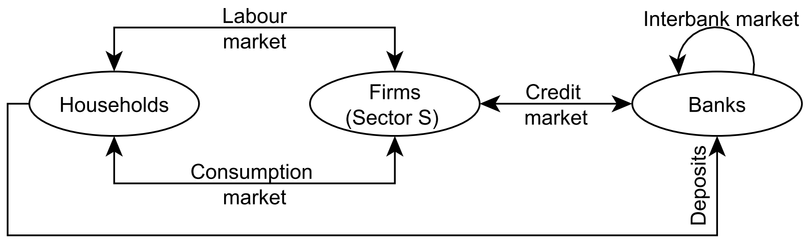


Figure 5.1: High-level view of agents' interactions

bank network and bipartite network of bank-firm links respectively.

The economy I consider comprises different sectors and each firm is assigned to a sector. I control the level of diversification (diversity) of the financial system using a single parameter that fixes the number of sectors each bank can lend to on the credit market. A time period in our model corresponds to 1 day in which the agents carry out the following sequence of operations or decisions. Our model belongs to the class of "one-step" models see Delli Gatti et al. 2011; Dosi et al. 2010; Klimek et al. 2015, for examples. In contrast, other works in the literature (Erlingsson et al. 2014b; Gaffeo et al. 2008; Lengnick 2013) use models that capture heterogeneous and real-world timescales . In our model, agents carry out the following sequence of operations or decisions in each time period.

1. Firms set their production and pricing strategies heterogeneously
2. Firms update their labour and loan demand accordingly.
3. Banks propose interest rates to firms heterogeneously and may raise liquidity to service loans.
4. Firms recruit (fire), produce goods and pay wages
5. Banks receive deposits from their customers
6. Households attempt to spend a proportion of their savings on consumption.
7. Banks and firms attempt to meet obligatory payments namely dividends, loan repayments and interests.

8. Illiquid firms are liquidated, and their assets shared pro-rata among creditors

9. Banks with negative equity are said to be insolvent and are bailed-in by their creditors and(or) customers

5.2.1 Firms

1. There are N_f firms in the model. Each firm is randomly assigned to a sector s and produces perishable goods [2]. The goods produced by firms are perfect substitutes for the consumer. There are N_s sectors in the model.

2. A sector in our model represents a conceptual group of random firms. A firm follows heuristic rules proposed in (Delli Gatti et al. 2011; Gualdi et al. 2015; Klimek et al. 2015) in setting its production and price targets. The rules are based on the demand for a firm's goods and average market price in its sector. In a nut shell, Equation 5.1 implies that if demand is lower than expected a firm will reduce its production target provided its price is less than the average price in its sector otherwise it reduces its price instead. The reverse is followed if the firm sold all its goods in the previous time step.

$$
\begin{aligned}
Y_i^T(t+1) &= Y_i(t)[1+\gamma_y \Gamma_i(t)] \quad \text{if} \quad \begin{cases} Y_i(t) = D_i(t) \quad \text{and} \\ p_i(t) > \bar{p}_s(t) \end{cases} \\
Y_i^T(t+1) &= Y_i(t)[1-\gamma_y \Gamma_i(t)] \quad \text{if} \quad \begin{cases} Y_i(t) > D_i(t) \quad \text{and} \\ p_i(t) < \bar{p}_s(t) \end{cases} \\
p_i(t+1) &= p_i(t)[1+\gamma_p \Gamma_i(t)] \quad \text{if} \quad \begin{cases} Y_i(t) = D_i(t) \quad \text{and} \\ p_i(t) < \bar{p}_s(t) \end{cases} \\
p_i(t+1) &= p_i(t)[1-\gamma_p \Gamma_i(t)] \quad \text{if} \quad \begin{cases} Y_i(t) > D_i(t) \quad \text{and} \\ p_i(t) > \bar{p}_s(t) \end{cases}
\end{aligned}
\tag{5.1}
$$

where $D_i(t)$ is the total demand for the goods produced by firm i at time t, and

$$\bar{p}_s(t) = \frac{\sum_i^s p_i(t) D_i(t)}{\sum_i D_i(t)} \tag{5.2}$$

[2] Perishable in this context means the unsold goods cannot be preserved for the next time period

$\bar{p}_s(t)$ is the average price of sold goods in sector s at time t, $\Gamma_i(t)$ is drawn from the uniform distribution $U[0,1]$ for each firm while γ_y & γ_p drawn from $U[0,1]$ represent the production and price adjustment parameter respectively. Y_i^T & Y_i denote the target and realised production of firm i. I assume that the case $Y(t) = D(t)$ also implies the case $Y(t) > D(t)$ in our implementation.

3. Each firm computes the required workforce to achieve its target Y_i^T based on the following production function.

$$Y_i^T(t) = \alpha L_i^d(t) \tag{5.3}$$

where $L_i^d(t)$ denotes the labour demand for firm i at time t

4. Each firm randomly approaches one of the registered banks in its sector for loans to cover its liquidity shortfall given by:

$$max(0, L_i^d(t)W_i(t) - C_i) \tag{5.4}$$

where C_i denotes the cash of firm i and W_i represents its wage.

5. As in (Klimek et al. 2015; Poledna and Thurner 2016), banks propose interest rates for each firm using an increasing function of the firm's financial fragility $\mathscr{L}_i$ defined as the ratio of its total debt to its cash i.e.

$$r_{b,i}(t) = r_0(1+\varepsilon)[1 + tanh(\mu \mathscr{L}_i(t))] \tag{5.5}$$

where r_0 is the baseline interest rate, ε is drawn from the uniform distribution $U[0,1]$ to capture bank variations such as investment strategy and μ is a constant that controls the sensitive of the process.

6. Each firm attempts to repay a percentage τ and the interest due on its loan. Our approach implies a decrease in the amount of debt repaid as only a percentage of the remaining debt is paid each time period. An alternative approach will require the firm to pay a fixed amount of the debt each time period. We use the former in-order to ensure ergodicity of the model for long time periods. Finally, if the firm makes a profit after meeting these financial obligations, it pays a certain percentage η of this profit to its owner.

5.2.2 Banks

1. There are N_b banks in the model. I consider a simplified structure for a typical bank's balance sheet as shown in Figure 5.2.

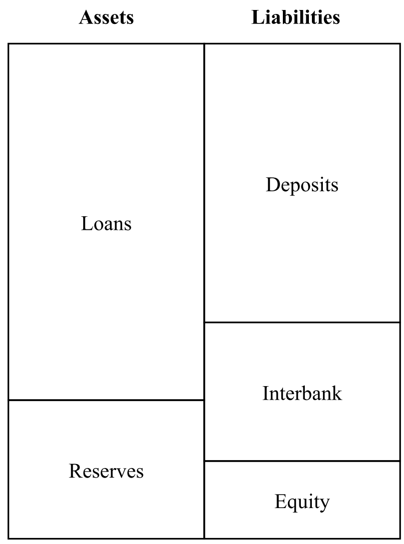
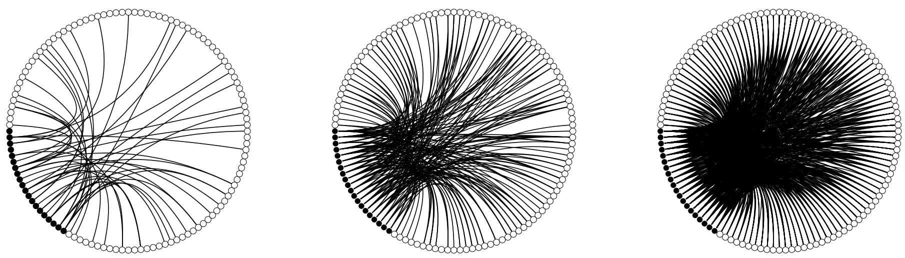


Figure 5.2: A stylised representation of a typical bank's balance sheet structure



(a) $\phi_s = 1$ (b) $\phi_s = 10$ (c) $\phi_s = 20$

Figure 5.3: Bank-firm network for different values of ϕ_s. Black circles: Banks. White circles: Firms.

2. A bank receives deposits from its customers. I assume that banks only receive deposits from households (including firm owners) but not from firms in-order to keep the model simple.

3. A bank can only provide loans to ϕ_s distinct sectors. I consider ϕ_s as a bank's diversification level and not its number of lending links with firms (i.e. its

degree). This approach implies that we can exogenously tune the level of diversification of banks using a single parameter such that $1 \leq \phi_s \leq N_s$. As such, banks become exposed to the same firms with increasing ϕ_s as shown in Figure 5.3. Specifically, I show the bank-firm networks for different values of ϕ_s in Figure 5.3.

4. I set $N_s = N_b$ in-order to create the case where all banks lend to all sectors and where all banks lend to distinct sectors.

5. A bank supplies the loan requested by firms. If the bank does not have enough cash to fulfil the due loan, it attempts to raise the shortfall from M_b other banks on the interbank market. If it is unable to raise the required cash, it resorts to the lender of last resort. This approach implies that banks can always raise enough cash to provide loans. While this assumption is rather simplified, it allows us to focus solely on the macroeconomic impact of diversification without mixing in cash constraint. I have also experimented with another version in which banks cannot raise cash from the central bank to provide loans and find that the qualitative features of the model are preserved, however the system state is not ergodic after $t = 1500$.

6. Each bank services the interest due on its interbank debt and repays a proportion τ of this debt. Our focus is on bank failures due to balance-sheet insolvency; thus, I abstract away from illiquidity by assuming that an illiquid bank that cannot raise cash from the interbank market can always resort to the central bank to cover its liquidity shortfall.

7. A bank is required to keep a percentage ζ of its total deposits in a reserve account at the central bank.

5.2.3 Households

As in (Delli Gatti et al. 2011; Gualdi et al. 2015; Klimek et al. 2015), households in our model are endowed with the following behaviours:

1. Each household is either a firm owner or a worker. A firm owner does not work but receives dividend payments each time period depending on whether or not its firm makes a profit. A worker supplies one unit of labour inelastically.

2. Each household is randomly assigned to a bank and continues to save its cash in this bank throughout the simulation.

3. At every time step, an employed household switches to a firm offering higher wages with probability φ. Unemployed workers are then randomly assigned to firms with vacancies.

4. Each household attempts to spend a proportion C_h of its savings in M_f randomly chosen firms. The selected firms are then approached in increasing order of their selling prices. Also, it is possible that a household's needs are not completely satisfied thus making the consumption market inefficient.

5.2.4 Contagion mechanism

The consumption market dynamic described above induces random shocks in the performance of firms. If a firm is unable to meets its financial obligations, its owner would try to cover the liquidity shortfall. In-case this is not sufficient, the firm is liquidated and its asset plus the owner's wealth is shared pro-rata among its creditors. The owner immediately starts a new firm with expected demand and price set to the average across all firms. This process may result in some of its creditors (i.e. banks) writing-off portions of the loans. This dynamic may cause one or more banks to fail.

A bank is deemed to have failed whenever its equity falls below zero (i.e. it becomes insolvent) due to loan defaults. A failed bank is resolved using a bail-in resolution tool see Benczur et al. 2017; Conlon and Cotter 2014; Hüser et al. 2017; Klimek et al. 2015, for elaborate discussions on bail-in. Basically, this involves restructuring the balance sheet of the failed bank such that some of its liabilities (interbank loans & deposits) are converted into equity.

I implement this by subtracting a one-time levy (required to cover the negative equity position) and a small overhead ξ (required to ensure continued bank operations) from its deposit and interbank loan accounts proportional to their sizes. Hence, the losses are borne by the bank customers and other banks that have provided loan to it on the interbank market in exchange for ownership rights. This procedure effectively creates a contagion channel through the bank-bank network and enables some of the bankruptcy cost to be borne directly by households.

5.3 Model Calibration and Validation

I initialise the model with parameters stipulated in Table 5.1 based on existing work in the literature (Gualdi et al. 2015; Klimek et al. 2015; Poledna and Thurner 2016). These works generally attempt to calibrate the model based on existing micro-founded behavioural studies as in (Geanakoplos et al. 2012; Hommes 2013). Gualdi et al. (2015) study the characteristics of the model in a space of parameters. They show for instance the existence of a phase transition from economic stability to instability that is robust to model modifications. Furthermore, Poledna and Thurner (2016) show that model can reproduce systemic risk profiles of the biggest banks in the Austrian financial system using the parameters in Table 5.1.

Consequently, the model is validated against its ability to reproduce an ensemble of stylized facts reported in real economies. In Figure 5.4, I show the emergence of interesting macro and microeconomic phenomena from the decentralised model dynamics. Specifically, in Figure 5.4a, we observe the emergence of alternation of booms and recessions in aggregate output like business cycles reported in real national GDP data. These cycles have been found to endogenously arise when the assumptions of perfect ex ante coordination and walrasian market clearing are relaxed (Gualdi et al. 2015; Lengnick 2013).

The top right panel shows a negative correlation between change in output ($\Delta Y = Y_t - Y_{t+1}$) and change in unemployment ($\Delta U = U_t - U_{t+1}$) consistent with Okun's law (Prachowny 1993). Beveridge's curve is shown to emerge from the model's labour dynamics in Figure 5.4c i.e. a negative relationship between vacancy

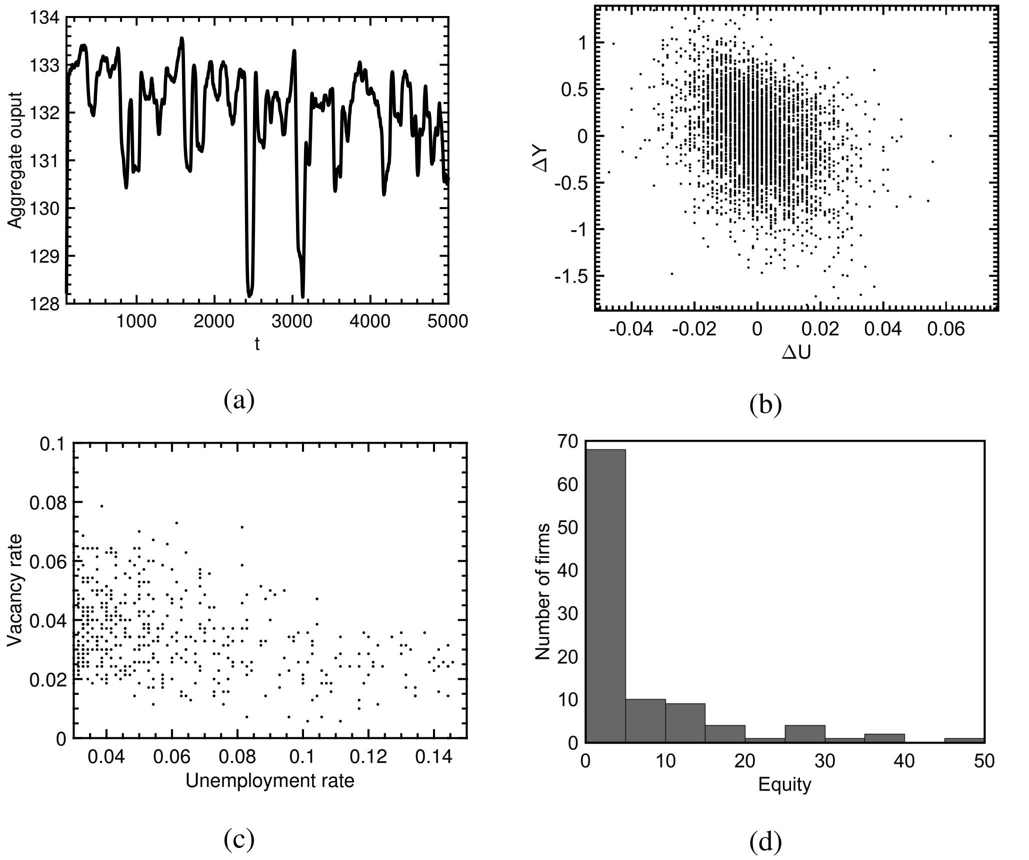


Figure 5.4: Emergent macroeconomic phenomena from a representative simulation. (a) Output (b) Okun's law (c) Beveridge curve (d) Power-law firm size distribution

rate (measured as the ratio of job openings to the number of employable households) and unemployment rate (Nickell et al. 1960). Finally, we observe the emergence of a power law distribution of firm sizes in Figure 5.4d consistent with empirical findings in real economies (Axtell 2001). Although, the agent based model I consider is simple, it still comes close to displaying phenomena observed in real economics emerging from the self-organising and complex interactions between the heterogeneous agents in an evolving system lacking central coordination without recourse to over-simplified assumptions of rationality, representative agents and general equilibrium.

5.4 Stability Analysis

In this section, I investigate the systemic and idiosyncratic risk inherent in the financial system based due to only the bank-firm network. Idiosyncratic risk refers to the probability of a one-off or isolated bank failure. The failure of Barings bank in 1995, for instance, was an isolated event and specific to Barings (see Fay 1997, for an elaborate discussion on this event). Systemic risk on the other hand refers to the probability of a large part of the financial system failing. A good example is the 2007 financial crisis during which major financial institutions like American International Group (AIG), Bear Stearns, Lehman Brothers, Citigroup etc. either failed or had to be saved from failing by different government intervention schemes (Bullard et al. 2009).

I measure systemic risk in terms of the probability of observing a global cascade of bank defaults (i.e. joint bank failures) while idiosyncratic risk refers to the probability of observing an isolated bank default in a simulation. In our analysis, a global cascade of defaults is said to occur if the number of bank failures exceeds a defined threshold θ. Unless otherwise stated, I define θ as 25% of the total number of banks and abstract from the impact of the bank-bank network by counting only bank failures before bail-in occurs in each time period. Moreover, I account for randomness present in the labour, consumption and credit market by averaging over 300 simulations with each simulation spanning 2500 time periods.

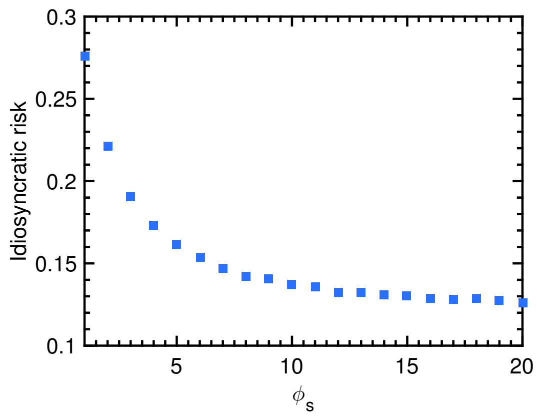
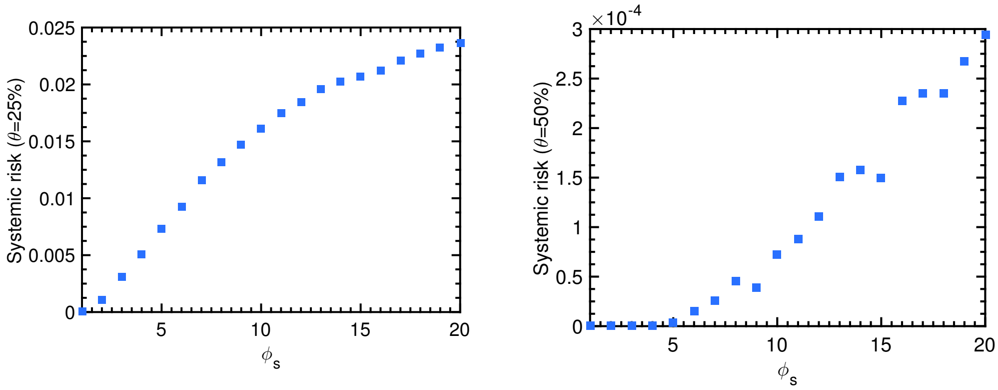


Figure 5.5: Emergent idiosyncratic risk as a function of ϕ_s due to only loan defaults using 300 simulations with each simulation spanning 2500 time periods.



(a) $\theta = 25\%$

(b) $\theta = 50\%$

Figure 5.6: Emergent systemic risk as a function of ϕ_s. Diversification increases systemic risk. Results remain qualitatively unchanged with respect to θ

Figure 5.5 reveals that idiosyncratic risk is decreasing with diversification. In contrast, Figure 5.6a shows that systemic risk is increasing with diversification. We find that the qualitative behaviour of this result is preserved by changing θ to 50% as shown in Figure 5.6b. These results are echoed in the recent work by Gurgone et al. (2018). The reason why increasing diversification appears to increase systemic risk but reduce idiosyncratic risk can be intuitively understood from the fact that banks become less diverse and increasingly exposed to the same sectors as they become more diversified (i.e. the bank-firm network becomes more connected) such that negative spill overs emanating from the real sector during a recession is able to affect many banks. However, diversification ensures that a bank's risk is not concentrated in any one sector such that the negative impact of downturns in a sector becomes smaller on the bank, effectively reducing the probability of the bank failing.

5.4.1 Impact of contagion

In the discussion above, I abstracted from the impact of contagion arising from the bank-bank network (i.e. links between banks) and concentrated only on the impact of the bank-firm network. In this section, I briefly characterise the joint impact of both network layers. The squares in Figure 5.7 denote systemic risk due to only the bank-firm network while the circles show the joint impact of the bank-firm and bank-bank networks. Thereby suggesting that the bank-bank network serves to amplify contagion in agreement with reports in (Caccioli et al. 2015; Lux 2016; Wagner 2010).

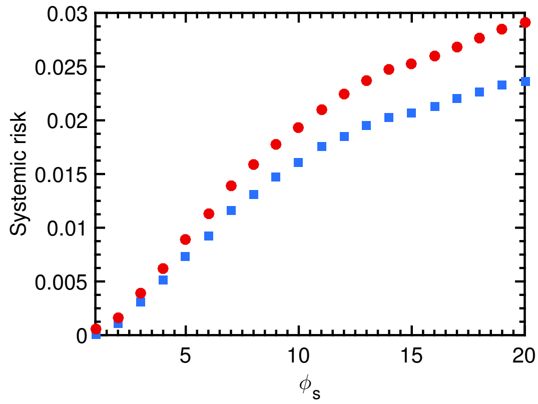


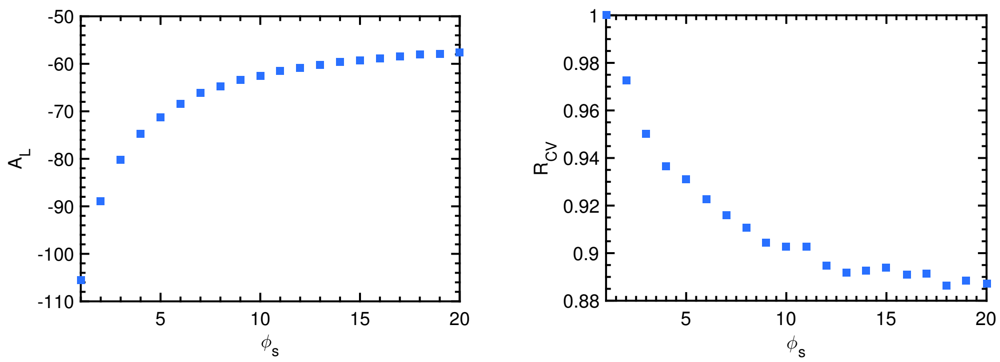
Figure 5.7: Emergent systemic risk as a function of ϕ_s. Squares: bank-firm network only. Circles: Joint impact of the bank-firm and bank-bank network.

Specifically, it appears the contagion impact of the bank-bank network becomes pronounced with increasing diversification. In contrast to natural expectations that diversification should reduce contagion spread from bank failures since it makes the banks individually safer. This follows from the fact that the negative spill over from the real economy would initially weaken more banks as they become more exposed to the same sectors such that additional losses suffered through the bank-bank network may easily trigger more cascading defaults.

5.4.2 Social cost

I measure social cost in terms of the average rate of losses from the financial system since this is the amount in Dollars that would be required if the banks were to be bailed out by the government with taxpayers' money. I define average rate of losses over a period T as $A_L = \overline{\sum_{t=1}^{T}} TotalSystemLiabilities_t - TotalSystemAssets_t$ and plot it as a function of ϕ_s in the left panel of Figure 5.8.

Our notation implies that increasing values denote greater loss. As such Figure 5.8 suggests that increasing diversification leads to higher social cost. Moreover, in the right panel of Figure 5.8, I show the impact of diversification on the real economy in terms of the aggregate credit volume. Specifically, I compare each level of



(a) Average rate of losses

(b) Relative credit volume

Figure 5.8: Average rate of losses and credit volume as a function of ϕ_s.

diversification relative to the completely un-diversified case (i.e $\phi_s = 1$). The plots suggest that diversification is having a negative impact on the real economy. This follows from the fact that diversification leads to a higher risk of the joint failure of many banks.

5.4.3 Robust yet fragile

The financial system has been shown to exhibit a "robust-yet-fragile" behaviour such that while the likelihood of a global cascade is low, the effects are usually widespread whenever it occurs (Caccioli et al. 2014; Gai and Kapadia 2010; Mistrulli 2011). I contribute to this strand of studies by investigating if our model also produces the "robust-yet-fragile" property? I do this by computing the conditional extent of cascades which I define as the average number of bank failures for the cases when global cascades occur.

In Figure 5.9, I plot the probability of a global cascade and the corresponding extent of cascades as a function of ϕ_s. We find that while global cascades are very unlikely, however, a large part of the financial system is hit whenever it occurs particularly for low levels of diversification. For instance, while the probability for a global cascade is almost negligible (i.e. 5.2267×10^{-4}) when $\phi_s = 1$, however, more than 25% of banks are hit whenever a global cascade does occur.

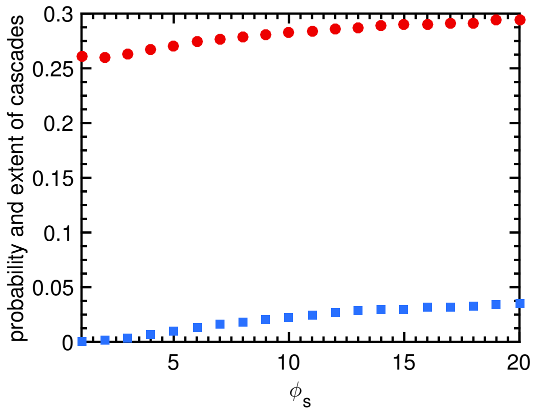


Figure 5.9: Probability and extent of global cascades as a function of ϕ_s. Squares: probability for global cascades. Circles: conditional extent of cascades.

5.4.4 Preferential bank-firm model

So far, I have characterised the stability of the system based on the bank-firm link formation process outlined in subsection 5.2.1. However, the work done by (Marotta et al. 2015; Masi and Gallegati 2012) suggests the presence of preferential lending relationships between banks and firms. In particular, they show that the degree distribution of banks in the bank-firm network is dependent on their balance sheet sizes such that the big banks tend to have more links with the real sector than small banks.

Moreover, empirical studies suggest that firms tend to form persistent links with certain banks in order to minimise agency cost and develop readily accessible credit lines (Agarwal and Ann Elston 2001; Ferri and Messori 2000; Fidrmuc et al. 2015; Temizsoy et al. 2015). It then becomes interesting to ask what is the stability impact of introducing this kind of preference structure into the network of loans from banks to firms? To address this question, I re-design the bank-firm lending relationship such that a firm in a sector s forms a lending relationship with bank b from the set B_s of banks registered in sector s with a probability p_{bf}. I compute p_{bf} as a function of the bank's balance sheet size A_b and the number of existing links between f and b (μ_{bf}) i.e.

$$p_{bf} = \frac{A_b \mu_{bf}}{\sum\limits_{b \in B_s} A_b \mu_{bf}} \tag{5.6}$$

This network formation process typically introduces a scale-free structure through the creation of a few banks with relatively higher degrees (i.e. more exposures to the real sector) than others. In Figure 5.10 and Figure 5.11, I compare the stability impact of this structure to our benchmark model using the same initial configuration and random number seed for respective simulations. I refer to the original bank-firm model outlined in subsection 5.2.1 as the benchmark model.

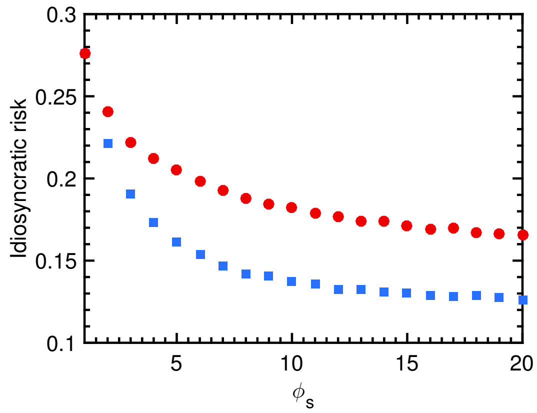


Figure 5.10: Emergent idiosyncratic risk as a function of ϕ_s. Squares: Benchmark model. Circles: Preferential model

We find that the emergent risk profiles retain the same features identified in the benchmark case (i.e. lower idiosyncratic risk and higher systemic risk with increasing diversification). However, the plot in Figure 5.10 suggests that preferential attachment induces more idiosyncratic risk into the system, especially for high levels of diversification. This follows from the fact that the preferential network formation process I consider results in some banks that are over-diversified (thus less likely to fail) and others that are under-diversified and more prone to default. This effectively increases the aggregate idiosyncratic risk in the financial system relative to the case of the benchmark model.

Furthermore, the plot in Figure 5.11 suggests that preferential attachment reduces systemic risk. This provides more credence to reports in the complex networks literature that show that scale-free networks comprising few highly connected nodes (i.e. hubs) and many nodes with low connectivity are more robust to random shocks (Albert et al. 2000; Albert et al. 2002; Caccioli et al. 2011; Gai et al. 2011).

The stability analysis from the benchmark simulation which shows that diversification reduces idiosyncratic risk while diversity decreases systemic risk provides an intuition for this result. Basically, the evolving preferential network effectively introduces more diversity into the system through the creation of many relatively isolated banks (i.e. banks with low degrees), which is desirable from the point of view of reducing the probability of joint failures (i.e. systemic risk).

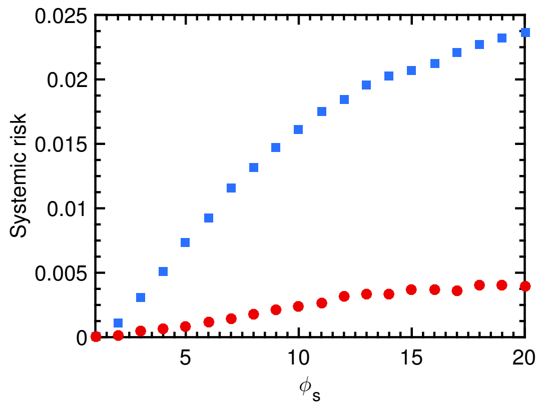


Figure 5.11: Emergent systemic risk as a function of ϕ_s. Squares: Benchmark model. Circles: Preferential model

5.5 Policy Impact Analysis

In the previous section, I showed that diversification reduces idiosyncratic risk, however, it also makes the financial system less diverse consequently leading to more joint failures (i.e. higher systemic risk). It then becomes interesting to ask if it is possible to design polices that permit diversification without exacerbating systemic risk?

A possible way of achieving this is to increase capital requirements of banks relative to their similarity with the rest of the financial system such that banks with higher degrees of similarity are required to more capital. Moreover, it is known from the literature that higher capital requirements improve the stability of the financial system. However, higher capital requirements come at a cost of reduced lending to the real sector (see Bridges et al. 2014; Brooke et al. 2015). As such, I investigate the possibility of an alternative regulatory policy that achieves the same objective without requiring banks to hold additional capital.

The policy I consider is motivated by the fact that a bank does not internalise the impact of its activities on the build-up of systemic risk in the financial system (Acharya 2009; Wagner 2010). I model this policy by defining a similarity measure S_b for bank b relative to the rest of the financial system as:

$$S_b = \sum_{a \in B_b} \frac{|F(b) \cap F(a)|}{\max(|F(b)|, |F(a)|)} \tag{5.7}$$

Where B_b is the set of banks registered in the same sector(s) as bank b and $F(x)$ gives the set of firms with lending relationship(s) with bank x. I further define ΔS_{bf} as the additional increase in the similarity for a bank b conditional on a credit transaction with a firm f. Finally, I implement a simple framework such that firms are more likely to transact with banks having lower ΔS_{bf}. Thus, deviating from the random bank-firm link formation process outlined in subsection 5.2.1. In particular, the framework is such that given ΔS_{bf} a firm f transacts with bank b with probability ω_{bf} defined as:

$$\omega_{bf} = \frac{1/\Delta S_{bf}}{\sum\limits_{a \in B_b} 1/\Delta S_{bf}}$$

$$\Delta S_{bf} = S_{bf} - S_b \tag{5.8}$$

Following the intuition developed in Equation 5.7, I define S_{bf} as:

$$S_{bf} = \sum_{a \in B_b} \frac{|(F(b) \cup f) \cap F(a)|}{\max(|(F(b) \cup f)|, |F(a)|)} \tag{5.9}$$

A possible way of implementing this policy is for a central bank to compute ΔS_{bf} and translate this into a tax that reduces lending activities of banks with high ΔS_{bf}. This could be in the form of a model that essentially increases the lending rates from such banks, which would ultimately incentive firms to transact with those banks with low ΔS_{bf}. Poledna and Thurner (2016), for instance, adopt a similar structure where the interest rate proposed by a bank is proportional to its ”debtrank”. However, I do not model this translation since our interest lies in understanding the effectiveness of the policy rather than its implementation details.

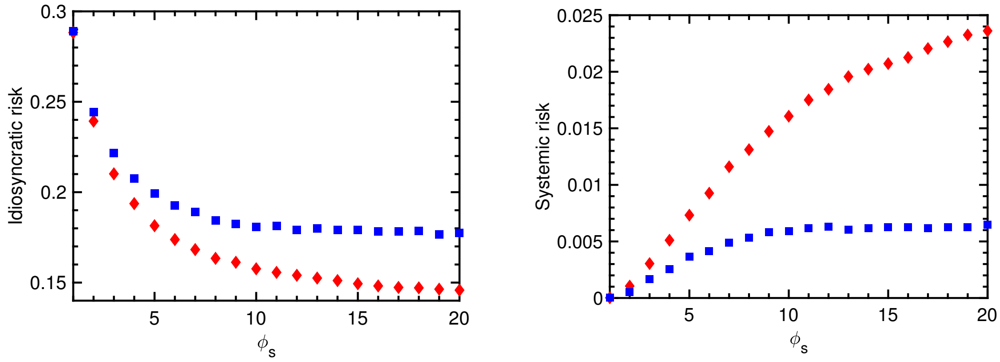


Figure 5.12: Idiosyncratic and systemic risk as a function of ϕ_s. Diamonds: Without policy. Squares: With policy. Results refer to 300 simulations with each simulation spanning 2500 time periods.

I compare the stability impact of this policy relative to our benchmark model using the same initial configuration and random number seed for respective simulations. The plots in Figure 5.12 show that the policy is effective at reducing systemic risk. This follows from the fact that the policy induces a self-arranging network topology between banks and firms that promotes dissimilarity in the financial system even with increasing diversification which ultimately reduces the build-up of systemic risk. Although, idiosyncratic risk is relatively higher with our policy however the benefit of this risk reducing with increasing diversification is preserved.

5.6 Conclusion

Banks are increasingly diversifying their balance sheets across several assets in order to reduce their individual riskiness (Battiston et al. 2012b; Wagner 2010). Accordingly, the true consequences of diversification particularly as it affects the stability of the financial system and the wider economy is actively being discussed by policy makers and academics (Battiston et al. 2012b; Caccioli et al. 2014; Tasca et al. 2014; Wagner 2008; Wagner 2010). I contribute to this discussion by studying the impact of diversification on systemic (i.e. likelihood of joint failures) and idiosyncratic risk (i.e. risk of a one-off failure) using an agent based model that couples the financial system and the real economy. This approach not only leads to the emergence of a constantly evolving interbank and bank-firm network but also results in the emergence of shocks from the real sector that can be transmitted to the financial system via the evolving multi-layered network of bank-firm and bank-bank lending relationships.

Our findings suggest that diversification reduces idiosyncratic risk but increases systemic risk. I note that this finding leads to a higher cost for the society which ultimately results in a negative feedback on the real economy in terms of lower aggregate credit volume. Moreover, we find the emergence of a ”robust yet fragile” behaviour from the model especially for low levels of diversification. This behaviour has been shown in several studies to characterise the financial system (Caccioli et al. 2014; Gai and Kapadia 2010) and simply implies that while the probability of a systemic crisis is low, the impact is however widespread (i.e. a large part of the financial system is affected) whenever it occurs. I then investigated the impact of introducing preferential attachment into the lending links of the bank-firm network and find that the risk profiles remain essentially the same as in the original model. However, we find that preferential attachment increases idiosyncratic risk but significantly reduces system risk in the financial system.

I then investigated the effectiveness of a regulatory policy that permits diversification without exacerbating systemic risk but does not require banks to hold additional capital. The policy essentially promotes bank-firm credit transactions that result in the smallest increase in the similarity between banks in the financial system. I show that this policy is effective at reducing systemic risk whilst keeping the benefit of diversification of reducing idiosyncratic risk. This is because the policy induces a self-arranging network topology between banks and firms that promotes dissimilarity in the financial system even with increasing diversification which ultimately reduces the build-up of systemic risk.

Finally, our analysis side-steps the impact of correlation between sectors even though correlation can endogenously arise in the model particularly during periods of economic downturns. Nevertheless, it would be interesting to extend this work to explicitly characterise the stability of the financial system on the joint impact of diversification and correlation. However, I note that the impact of correlation would be irrelevant at the point where each bank becomes fully diversified across all the sectors.

Parmeter	Description	Value
	Model Parameters	
N_h	Number of households	800
N_f	Number of firms	100
N_b	Number of banks	20
N_s	Number of sectors	20
ϕ_s	Bank diversification level	Variable
τ	Loan & interest repayment	0.05
η	Firm dividend	0.25
r_m	Interest rate threshold	0.05
μ	Interest rate adjustment parameter	0.01
M_{ib}	Number of banks approached on the interbank market	2
M_f	Number of firms approached on the consumption market	2
α	Labour productivity	0.02
C_h	Consumption budget	0.8
ψ	Labour turnover probability	0.05
γ_y	Production adjustment parameter	0.1
γ_p	Price adjustment parameter	0.1
z	Wage adjustment parameter	0.001
ζ	Reserve requirement	0.03
ξ	Resolution overhead	1

Table 5.1: Model simulation parameters

Chapter 6

Policy Interactions

6.1 Introduction

Banking regulation and supervision has witnessed radical changes since the recent global financial crisis. The crisis exposed the inherent limitations of existing regulatory frameworks and precipitated calls for additional and new policy overlays to improve the stability of the financial system. The result has been a paradigm shift from policies focused exclusively on achieving micro-prudential resilience to macroprudential policies that place more emphasis on system-wide stability especially beyond the context of the financial system. In this light, the Basel Committee on Banking Supervision (BCBS) proposed new banking regulations namely Basel III to address the shortcomings of the previous Basel II regulatory framework (see Basel Committee On Banking Supervision 2011).

Moreover, the question of how to resolve a failed financial institution also came under serious controversial debates in the wake of the financial crisis with some policy makers promoting government bail-outs while others adopted the use of bail-ins. For instance, the United States government faced increased backlash over its use of tax-payers' money to fund bail-out rescue missions for certain banks deemed "too big to fail" (TBTF) with many suggesting that such bail-outs only provided more incentives for such banks to take on additional risks with the reassurance that tax-payers would eventually bear the cost (Nagourney 2009). On the counter side, proponents for bailouts have pointed to the contagion risk channel embedded with a bail-in resolution regime. To further complicate matters, policy makers still must address the traditional question of what monetary policy rule to implement in-order to adjust the interest rate in response to changes in inflation and economic activity. For instance, a central bank whose sole objective is to control the inflation level may choose to adopt an inflation-targeting monetary policy.

The combination of these regulatory policies (i.e. monetary, resolution and macroprudential) without understanding the feedback system underlying their interactions may contradict the initial objective of the regulator and even result in unintended consequences on financial stability and the wider economy. Addressing these questions is desirable from the point of view of economic policy makers and world leaders who according to Farmer and Foley (2009) were said to be "flying the economy by the seat of their pants" during the recent financial crisis.

Unfortunately, these regulatory policies have mostly been studied in isolation until recently thus bearing the fallacy of composition risk. In particular, the literature on prudential regulation focused mostly on capital adequacy requirement *CAR* has received the widest attention from academia and industry over the last decade. Cosimano and Hakura (2011), Gauthier et al. (2012), Miles et al. (2013), Ryo et al. (2010), and Slovik and Cournède (2011) provide empirical evidence of a positive impact of the *CAR* instrument on the economy and the stability of the financial system while Angelini and Clerc (2011), Boissay (2011), Derviz (2013), and Dib (2010) employ general equilibrium/dynamic stochastic general equilibrium based models to also investigate the qualitative impact of prudential regulation on the economy and financial stability. A growing number of recent studies have adopted the use of agent based computation models for macro/financial economics studies (Ashraf et al. 2011; Cincotti et al. 2010; Dawid and Hoog 2015; Dosi et al. 2015; Krug et al. 2014; Raberto and Teglio 2012; Tesfatsion 2005). The literature on bankruptcy resolution is rather sparse. Siegert et al. (2015) provides a concise review of the methodologies for estimating the implicit subsidies enjoyed by TBTF banks concisely while Klimek et al. (2015) provides a comparative assessment of the macroeconomic impact of different resolution regimes. A recent trend of research work attempt to understand the interaction of alternative macroprudential regulations and monetary policy (Agenor et al. 2013; Angelini et al. 2012; Angeloni and Faia 2013; Beau et al. 2012; Napoletano et al. 2015; Spencer 2014; Suh 2014).

I contribute to this strand of literature by studying the long term economic impact of different bank resolution instruments used by regulators in the presence of prevailing monetary and macroprudential policies using an agent based model that couples the real economy and the financial system. Our choice of agent based modelling is informed by the need to capture the economy as a complex evolving system lacking central co-ordination. Thus allowing for the emergence of out-of-equilibrium phenomena at the macro level such as financial crises (Bookstaber 2012; Tesfatsion 2005) which cannot simply be observed by aggregating over a representative agent as typified in the alternative traditional neoclassical equilibrium models. These models are not suitable for modelling the emergence of unforeseen macro-properties from complex interactions due to the assumptions of rationality, representative agents and equilibrium that facilitate their mathematical tractability. Some critiques have even argued that the very notion of a crisis and the use of representative agents, equilibrium and assumption of rationality is by nature contradictory (Fagiolo and Roventini 2012; Farmer and Foley 2009)

Our agent based model implements a self-organising closed economy populated by heterogeneous agents including firms, households, banks and a central bank interacting within different markets with bounded rationality. Households interact with firms in the labour and consumption market while firms and banks interact within the credit market. The central bank is responsible for setting monetary and macroprudential policies whilst also handling the resolution of failed banks. I consider Basel II and Basel III as the possible prudential frameworks, bailout, bail-in, purchase & assumption (P&A) as the alternative resolution tools and single, dual and triple rules respectively targeting inflation, unemployment & inflation, unemployment, inflation & credit volume as the alternative monetary policy rules available to the central bank. These complex interactions lacking central coordination result in the emergence of recurrent phenomena observed in real economies. Specifically, the model can reproduce economic trends found in Okun (Prachowny 1993) and Beveridge curves (Nickell et al. 1960). Moreover, we observe the emergence of alternation of booms and recession in aggregate output, power law distribution of firm sizes (Axtell 2001) and realistic co-movements of macroeconomic variables namely unemployment, inflation and the nominal interest rate.

We find that Basel III does not always improve the stability of the financial system relative to Basel II. Specifically, we find that Basel III produces more bank defaults when the central bank follows an inflation targeting monetary rule but reduces the frequency of defaults if the monetary policy rule also responds to changes in unemployment and credit volume. Moreover, we find that the bailout regime results in the worst performance in terms of unemployment and output relative to other investigated resolution regimes. Also, we observe the least bankruptcy frequency under a P&A regime due to the emergence of bigger and more stable banks that are better able to absorb losses originating from loan defaults. Finally, we find that the Basel III components are not addictive under a P&A regime since this regime decreases the number of banks which further reinforces the reduction in lending already implied by the additional regulatory constraints on the active banks. Furthermore, the performance of Basel III framework is mainly characterised by the capital overlay components namely capital adequacy ratio and conservation buffer while the additional constraint imposed by leverage requirement does not seem to have any reasonable impact on the performance of the framework.

The rest of this chapter is organised as follows. In Section 6.2, I describe the model dynamics with detailed explanations of the resolution tools, Basel frameworks and monetary policies. I discuss the simulation results in Section 6.4 and summarise our findings in Section 6.5.

6.2 Model

I implement an extension of the model developed in the previous chapter to include a central bank agent that sets and enforce rules for bankruptcy resolution, prudential and monetary policies. Moreover, I make changes to the firm model to capture the influence of interest rate. Figure 6.1 provides a high-level view of the agents and their interactions within the model. The model is implemented to ensure stock flow consistency such that every liability on an agent's balance sheet is an asset on some other agent's books (see Figure 6.2, for a detailed description of each agent's balance sheet). As in the previous chapter, I validate the model against its ability to reproduce several stylized facts reported in real economies. We find that the model can reproduce economic trends described in Okun (Prachowny 1993) and Beveridge curves (Nickell et al. 1960). Moreover, we observe the emergence of alternation of booms and recession in aggregate output, power law distribution of firm sizes (Axtell 2001) and realistic co-movements of macroeconomic variables namely unemployment, inflation and the nominal interest rate. See Section 6.3 for an elaborate discussion on the model calibration and validation.

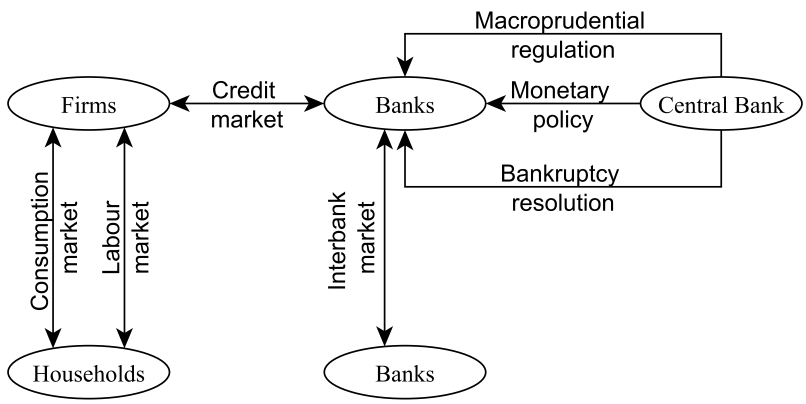


Figure 6.1: High-level view of Agents interactions. The central bank sets bankruptcy resolution, prudential and monetary rules

6.2.1 Firm behaviour changes

1. Each firm randomly approaches M_b banks for loans to cover its liquidity shortfall i.e. $max(0, L_i^d(t)W_i(t) - C_i)$, where W_i & C_i denote the pay and cash of firm i. The bank offering the best interest rate is selected. Banks propose interest rates for each firm using an increasing function of the firm's financial

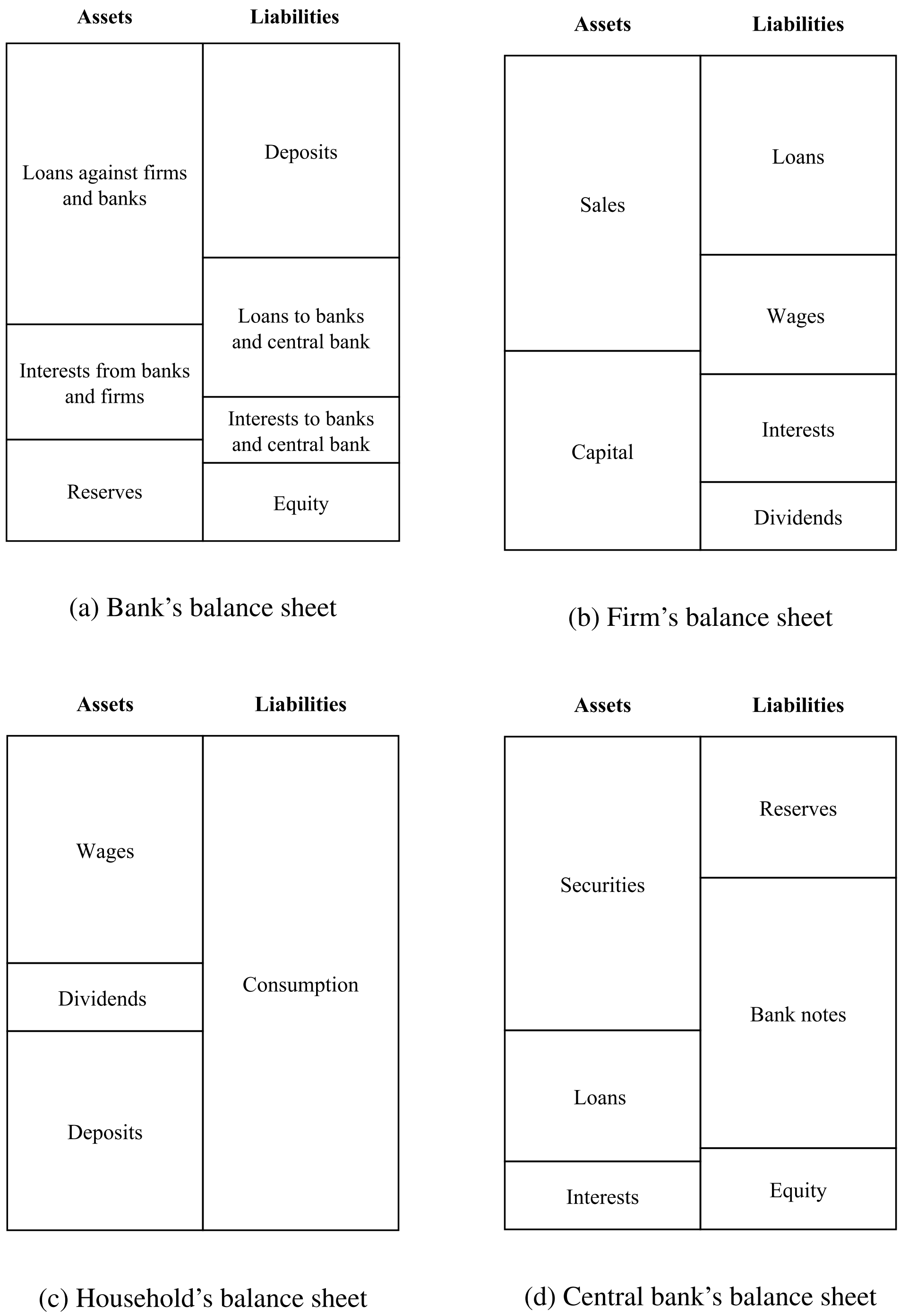

Assets
Liabilities
Loans against firms and banks
Interests from banks and firms
Reserves
Deposits
Loans to banks and central bank
Interests to banks and central bank
Equity
(a) Bank's balance sheet
Assets
Liabilities
Sales
Capital
Loans
Wages
Interests
Dividends
(b) Firm's balance sheet
Assets
Liabilities
Wages
Dividends
Deposits
Consumption
(c) Household's balance sheet
Assets
Liabilities
Securities
Loans
Interests
Reserves
Bank notes
Equity
(d) Central bank's balance sheet

Figure 6.2

fragility $\mathscr{L}_i$ defined as the ratio of its total debt to its cash i.e.

$$r_{b,i}(t) = r_0(t)(1+\varepsilon)[1+tanh(\mu\mathscr{L}_i(t))] \tag{6.1}$$

Moreover, a firm demands only a certain percentage Φ of the initial required loan if the interest rate exceeds r_m, where Φ is the credit contraction parameter and r_m is the maximum interest rate. i.e.

$$LoanDemand_i(t) = \begin{cases} \Phi LoanRequired & \text{if } r_{b,i} > r_m \\ LoanRequired & \text{otherwise} \end{cases} \tag{6.2}$$

2. Each firm updates its wages for the next period using similar heuristics as in the production & price update rule i.e.

$$W_i^T(t+1) = W_i(t)[1+\gamma_w\varepsilon\Gamma_i(t)] \; if \begin{cases} Y_i(t) < D_i(t) \\ \mathscr{P}_i(t) > 0 \end{cases} \tag{6.3}$$

$$W_i(t+1) = W_i(t)[1-\gamma_w u\Gamma_i(t)] \; if \begin{cases} Y_i(t) = D_i(t) \\ \mathscr{P}_i(t) < 0 \end{cases}$$

where $u = 1-\varepsilon$ is the unemployment rate and $\gamma_w = z\gamma_p$ is the wage adjustment parameter; $\mathscr{P}_i(t) = min(D_i(t), Y_i(t)p_i(t) - W_i(t)Y_i(t)$ is the profit of firm i at time t and γ_i is drawn from the uniform distribution $U[0,1]$. The intuition behind the above rules is that a firm would only consider increasing its wages for the next time step only if it makes a profit and the expected demand is met. Moreover, the firm would reduce its wages if it makes a loss and the demand for its goods is lower than expected. The wage adjustment parameter is also dependent on the level of unemployment such that low unemployment (high employment) would lead to higher wage increments and vice versa.

6.2.2 Monetary policies

The central bank follows Taylor (1993) rules to adjust the interest rate r_0 in response to changes in inflation & economic activity [1]. The idea behind the rules is straightforward, if i is the short-term interest rate and $i*$ some target rate, deviations of i

[1]By setting the interest rate at which bank can borrow from the discount window, the central bank automatically sets a ceiling for interbank rates and the credit market baseline rate in the model

from $i*$ is set proportional to the deviation of another variable z from the desired target $z*$ i.e.

$$i - i* = \theta_z(z - z*) \tag{6.4}$$

where θ_z is the adjustment parameter. In the model, I focus on inflation, unemployment and credit growth as target variables and discuss them under the following headings:

Single mandate rule(TR_π) The baseline rate r_0 is updated by only considering the deviation of the prevailing inflation rate from the desired target.

$$\ln(1 + r_{0,t}) = max\{\ln(1 + r*) + \phi_\pi(\ln(1 + \pi_t) - \ln(1 + \pi^*)), 0\} \tag{6.5}$$

Dual mandate rule($TR_{\pi,u}$) The central bank sets the baseline rate r_0 in response to deviations of the prevailing inflation and unemployment rates from their desired targets (Dosi et al. 2015).

$$\ln(1+r_{0,t}) = max\{\ln(1+r*) + \phi_\pi(\ln(1+\pi_t) - \ln(1+\pi^*)) + \phi_u(\ln(1+u^*) - \ln(1+u)), 0\} \tag{6.6}$$

Triple mandate rule($TR_{\pi,u,c}$) As in (Napoletano et al. 2015), I consider a variant of the Taylor rule where the central bank considers the change in credit volume as well as the deviations of the prevailing inflation and unemployment rates from their desired targets in setting r_0.

$$\begin{split}\ln(1+r_{0,t}) = max\{\ln(1+r*) + \phi_\pi(\ln(1+\pi_t) - \ln(1+\pi^*)) + \phi_u(\ln(1+u^*) - \ln(1+u)) \\ + \ln(\frac{C_t}{C_{t-1}})^{\phi_c}, 0\}\end{split} \tag{6.7}$$

6.2.3 Macroprudential policy

Most central banks around the world have built their macroprudential policy based on recommendations specified in the Basel framework issued by the Basel Committee on Banking Supervision(BCBS). In this work, I would consider the earlier Basel II and the more recent Basel III frameworks. Essentially, both frameworks seek to make the financial system more resilient to adverse shocks in a way that minimises negative spill-overs to the real economy.

Basel II The original Basel II framework requires a bank to hold total capital that is at least 2% of its risk weighted assets (RWA) [2]. In other words, the framework defines the minimum capital requirement for a bank at time t as:

$$CAR2 = \frac{TotalCapital_t}{RWA_t} \geq \chi_2, \tag{6.8}$$

with $\chi_2 = 2\%$. In our model, the assets of each bank including loans to firms, interbank loans and cash are weighted based on specifications in the Basel framework in which a weight is assigned to an asset class based on its probability of default such that a safe asset like cash is assigned a weight of zero [3].

Basel III The Basel committee developed this new framework to correct the shortcomings associated with Basel II. In the following, I discuss the components of the Basel III framework that are relevant to our analysis.

1. Minimum capital requirement (CAR3): Under Basel III, banks are required to hold capital that is at least $\chi_3 = 4.5\%$ of their risk weighted assets (up from 2% specified in Basel II). Also, the only qualifying capital under this new framework is common equity (Tier 1).

$$CAR3 = \frac{Tier1_t}{RWA_t} \geq \chi_3 \tag{6.9}$$

2. Liquidity requirement (LCR): A bank that is adequately capitalised can still be exposed to liquidity risk due to maturity mismatch between its lendings and borrowings. Under Basel III, the BCBS specifies a minimum liquidity coverage ratio in-order to improve the resilience of banks to short term liquidity risk and prevent the need for fire sales. In this framework, a bank is expected to hold an adequate stock of unencumbered high quality liquid assets (HQLA) that can cover for its expected net cash outflows (NCOF) over a

[2] While total capital includes other forms of qualifying and supplementary capital in addition to core equity, I only consider the latter in our model due to the simplified nature of our banks' balance sheets

[3] Interbank loans and firm credits are assigned weights of 100% respectively while cash is assigned a weight of 0% in our model

30 day stress scenario [4] i.e.

$$LCR = \frac{HQLA_t}{NCOF_t} \geq \gamma, \tag{6.10}$$

with $\gamma = 1$. The stress scenario simulates funding withdrawals and loan defaults by specifying run-off and default rates for liabilities and assets respectively. Specifically, interbank funding are assumed not to be rolled over (i.e. $v_{L_b} = 100\%$ run-off rate) while retail deposits are assumed to run-off at a $v_d = 10\%$. rate. On the asset side, interbank loans are given default rates of $v_{L_b} = 100\%$, Loans to firms are assumed to default at a rate of $v_{L_f} = 50\%$ while cash has 0% default rate . Hence, the expected cash outflows $E[C_t^-]$ and inflows $E[C_t^+]$ are computed as:

$$\begin{aligned} E[C_t^-] &= C_t^- + \sum_{i=1}^{n} v_i l_{i,t} = C_t^- + v_d D_t + v_{L_b} L_{b,t}^- \\ E[C_t^+] &= C_t^+ - \sum_{i=1}^{n} v_i a_{i,t} = C_t^+ - v_{L_f} L_{f,t} - v_{L_b} L_b^+ \end{aligned} \tag{6.11}$$

where C_t^- refers to due interest and loan payments while C_t^+ denotes interest and loan receipts, the net cash outflow ($NCOF_t$) is:

$$NCOF_t = E[C_t^-] - E[C_t^+] \tag{6.12}$$

3. Capital conservation buffer(CConB): Basel II is procyclical in the sense that a bank can easily satisfy the CAR requirement during upswings in the financial cycle. However, a downward change in the cycle can quickly erode its capital and cause it to deleverage in-order to comply with the CAR. CConB addresses this procyclicality by requiring a bank to hold additional 2.5% core capital above the regulatory minimum of 4.5% of RWA such that the bank would have more capital to drawn from during "bad" times. Moreover, instead of having to deleverage as in CAR, the bank is forced to retain future earnings (i.e. cut dividend payments) whenever it fails to comply with this requirement. This additional capital can be used to absorb the losses until the conservation buffer is restored without triggering a deleveraging cycle.

[4] A time period in our model typically corresponds to 1 month

4. Counter-cyclical capital buffer (CCyB): This serves as a macroprudential instrument that allows regulators to extend the capital conservation buffer by an additional 2.5% during upswings in the financial cycle and to suspend it during downturns in the financial cycle. The CCyB achieves the broader aim of protecting the financial system from periods of excessive credit growth often associated with the build of system-wide risk. I model the CCyB as a linear function of the difference between the credit-to-GDP ratio and its long-term trend estimated using a linear regression model based on data from the last 100 periods. Formally, the additional CCyB at time t is defined as:

$$CCyB_t = \begin{cases} 0 & \text{if } G_t \leq J \\ \frac{(G_t - J)}{(H - J)} * 0.025 & \text{if } J \leq G_t \leq H \\ 0.025 & \text{otherwise} \end{cases} \tag{6.13}$$

Where J and H denote the adjustment thresholds specified as $J = 2$ and $H = 10$ in the Basel framework.

5. Leverage requirement (LR): The leverage requirement places an upper bound on the growth size of a bank's balance sheet to prevent massive deleveraging during periods of downswings in the real economy. It is like the risk weighted CAR approaches discussed above except that the assets are now non-risk weighted i.e.

$$LR = \frac{Tier1_t}{TotalAssets_t} \geq \omega, \tag{6.14}$$

with $\omega = 3\%$.

6. Capital surcharges for SIBs. Banks tend to increase in size and complexity in-order to take advantage of the implicit subsidies associated with the so-called ”Too Big to Fail” status. This causes a moral hazard problem that leads to increased risk taking, interconnectedness and transactions via the payment system which may make increase the fragility of the financial system. Hence, the Basel committee has proposed imposing additional capital

requirements to a bank based on its level of systemic relevance (Basel Committee On Banking Supervision 2013). In their approach, banks are assigned weighted scores using five indicators including size, interconnectedness, substitutability, cross-jurisdictional activity and complexity. Based on the scores, the Basel committee proposes that four equally sized buckets are set between a chosen cut-off score and the maximum score. The banks are then placed in different buckets and each bucket is assigned a specific capital addon as shown in Table 6.1. The balance sheet composition of our banks only allows

Bucket	Score Range	Minimum additional loss absorbency capital
5(empty)	above D	3.5%
4	C-D	2.5%
3	B-C	2.0%
2	A-B	1.5%
1	cut-off A	1.0%

[5]

Table 6.1: Capital surcharges for SIBs

us to capture the first three (i.e. size, interconnectedness and substitutability) in computing the systemic score of a bank i.e.

$$Score_{i,t} = \frac{1}{3}\sum_{k=1}^{3} s_{i,t}^{k} \tag{6.15}$$

where each indicator $(s_{i,t}^{k})$ is defined as follows:

(a) Size. The size indicator weighs each bank based on its balance sheet size relative to the whole system i.e.

$$s_{i,t}^{1} = \frac{TotalAssets_{i,t}}{\sum_{j=1}^{n} TotalAssets_{j,t}} \tag{6.16}$$

[5] Banks whose systemic scores fall below the cut-off are not required to hold additional capital. The 5^{th} bucket is initially empty and serves to disincentives banks with high systemic scores from becoming even more systemically relevant. A new empty bucket would be required if the 5^{th} bucket becomes populated

(b) Interconnectedness. This provides a measure for the systemic relevance of a bank on the interbank network by summing the relative volume of funds granted and received by each bank via the interbank market together with the proportion of the bank's assets funded by interbank borrowings. Formally;

$$s_{i,t}^{2} = \left(\frac{Loans_{i,t}^{IB}}{\sum_{j=1}^{n} Loans_{j,t}^{IB}} + \frac{Credits_{i,t}^{IB}}{\sum_{j=1}^{n} Credits_{j,t}^{IB}} + \frac{Credits_{i,t}^{IB}}{\sum_{j=1}^{n} TotalLiabilities_{j,t}} \right) \Big/ 3 \tag{6.17}$$

(c) Substitutability. This gives an indication of the relevance of a bank in ensuring proper functioning of the payment system. I measure the substitutability of a bank as the relative cash transactions sent by the bank aggregated over a period t.

$$s_{i,t}^{3} = \frac{PaymentsSent_{i,t}}{\sum_{j=1}^{n} PaymentsSent_{i,t}} \tag{6.18}$$

6.2.4 Bankruptcy resolution

The central bank is responsible for resolving a failed bank. A bank is said to have failed whenever its equity position falls below zero. In this analysis, I am interested in understanding how the monetary policies and Basel regulations discussed above interact with following resolution strategies used mostly during 2008 financial crisis:

Purchase & Assumption (P&A). I follow the implementation of a P&A used in Klimek et al. (2015) which involves the transfer of a failed bank's operations to other healthy banks in the system. Specifically, the failed bank's assets and liabilities are acquired by each of the healthy banks proportional to their level of equity. Thus, it is important that households' deposit accounts and firm loan accounts are registered with the assuming banks to ensure model consistency.

Bailout. In a bailout, the government re-capitalises the insolvent bank with a sum sufficient to cover for its negative equity position and a small overhead ξ to ensure proper resumption of the bank's operations using taxes received from firms, banks & households. Hence, a bailout ensures continued operation of the failed bank in contrast to a P&A. I do not explicitly include a government agent in our model instead I impose a one-time levy over all households and firms proportional to their wealth and liquidity respectively in-order to raise the required bailout cash.

Bailin. A bail in involves restructuring the balance sheet of the failed bank such that some of its liabilities (loans & deposits) are converted into equity. I implement this by subtracting a one-time levy required to cover for negative equity position and a small overhead ξ to ensure continued bank operations from its deposits and interbank liabilities proportional to their sizes. Hence, the losses are borne by the bank customers and other banks that have provided loan to it on the interbank market in exchange for ownership rights in the bank.

6.3 Model Calibration and Validation

I validate the model against its ability to reproduce some stylized facts reported in real economies using a baseline scenario that combines a bailout resolution regime, Basel II and a single mandate monetary policy. In Figure 6.3, I show the emergent macroeconomic dynamics from a representative simulation using the benchmark scenario. Although, the agent based model is simplified, it still comes close to displaying out-of-equilibrium phenomena observed in real economics based on self-organising and complex interactions between the heterogeneous agents in an evolving system lacking central coordination without recourse to over-simplified assumptions of rationality, representative agents and general equilibrium.

Specifically, we observe the emergence of alternation of booms and recessions in aggregate output as reported in national GDP data in Figure 6.3a and Figure 6.4a, these business cycles have been found to endogenously arise when the assumptions of perfect ex ante coordination and walrasian market clearing are relaxed (Gualdi et al. 2015; Lengnick 2013). We observe in Figure 6.3a that while no assumptions of market clearing equilibrium has been imposed the economy self-organises towards full potential (i.e. productivity$(\alpha) \times N_h$). Figure 6.3c shows that unemployment rate ranges between 0% & 12%, which comes to close to what is observed in reality. Finally, inflation rate oscillates around the central bank's 2% target with

Parmeter	Description	Value
	Model parameters	
N_h	Number of households	800
N_f	Number of firms	100
N_b	Number of banks	20
τ	Loan & interest repayment	0.05
Φ	Credit contraction parameter	0.75
η	Firm dividend	0.25
r_m	Interest rate threshold	0.05
μ	Interest rate adjustment parameter	0.01
M_b	Number of banks approached on the credit market	2
M_{ib}	Number of banks approached on the interbank market	2
M_f	Number of firms approached on the consumption market	2
α	Labour productivity	0.02
C_h	Consumption budget	0.8
ψ	Labour turnover probability	0.05
γ_y	Production adjustment parameter	0.1
γ_p	Price adjustment parameter	0.1
z	Wage adjustment parameter	0.001
	Macroprudential policy parameters	
ζ	Reserve requirement	0.03
ω	Leverage requirement	0.03
γ	Liquidity requirement	1
χ_2	Minimum capital requirement for Basel II	0.02
χ_3	Minimum capital requirement for Basel III	0.045
$CConB$	Capital conservation buffer	0.025
J	Minimum adjustment threshold for CCyB	0.2
H	Maximum adjustment threshold for CCyB	1
	Monetary policy parameters	
π^*	Target inflation rate	0.02
u^*	Target unemployment rate	0.05
r^*	Target nominal interest rate	0.02
ϕ_π	Inflation adjustment parameter	0.15
ϕ_u	Unemployment adjustment parameter	0.11
ϕ_c	Credit adjustment parameter	0.07
	Bankruptcy resolution parameters	
ξ	Resolution overhead	1

Table 6.2: Model simulation parameters

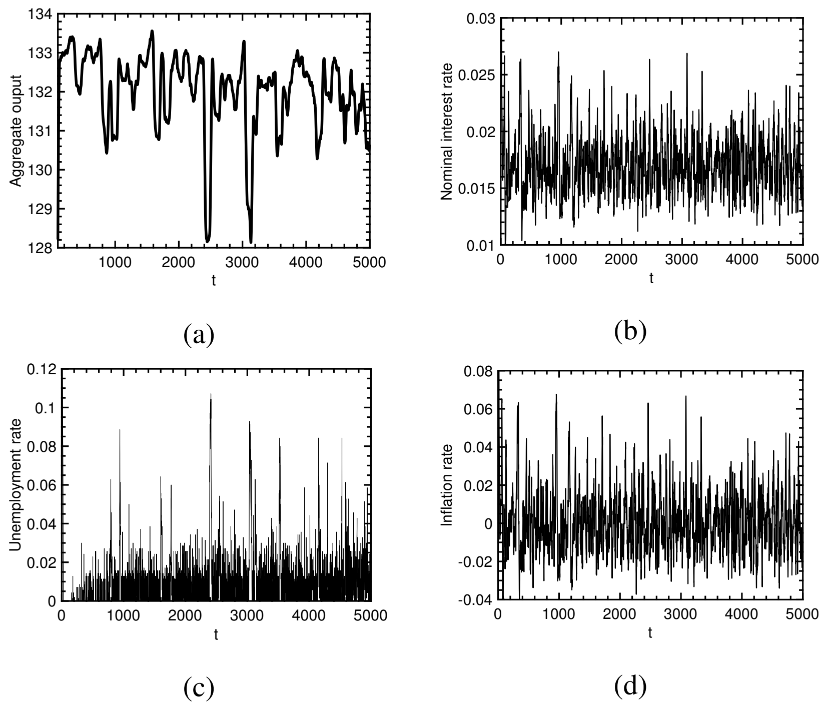


Figure 6.3: Emergent macroeconomic dynamics from a representative simulation using the baseline model. (a) Real output (i.e. adjusted for inflation) (c) Unemployment rate (d) baseline interest rate set by the central bank and (e) Inflation rate measured as the growth rate of the average prices across all firms.

occasional deflationary periods while the baseline interest rate maintains ergodicity around a reasonable range over a long period of time in Figure 6.3d and Figure 6.3b respectively.

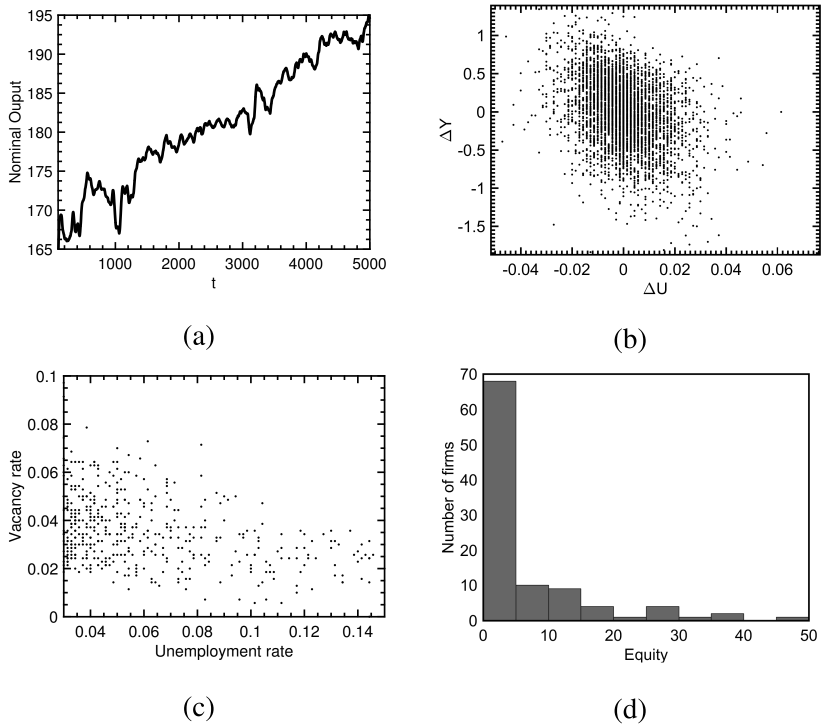


Figure 6.4: Emergent macroeconomic phenomena from a representative simulation using the baseline model. (a) Nominal output (b) Okun's law (c) Beveridge curve (d) Power-law firm size distribution

Furthermore, we observe the emergence of other interesting macroeconomic phenomena from the decentralised model dynamics in Figure 6.4. The top right panel shows a negative correlation between change in output ($\Delta Y = Y_t - Y_{t+1}$) and change in unemployment ($\Delta U = U_t - U_{t+1}$) consistent with Okun's law (Prachowny 1993). Beveridge's curve is shown to emerge from the model's labour dynamics in Figure 6.4c i.e. a negative relationship between vacancy rate (measured as the ratio of job openings to the number of employable households) and unemployment rate (Nickell et al. 1960) [6]. Finally, we observe the emergence of a power law

[6] While the negative correlation between the two variables seems low, our analysis shows that it is statically significant i.e. the p-value is less than .05

distribution of firm sizes in Figure 6.4d consistent with empirical findings in real economies (Axtell 2001).

6.4 Results and Discussion

I provide the model parameters in Table 6.2 and then the comparative analysis of the interactive impact of the regulatory tools discussed above including monetary policies, Basel regulations and resolution regimes relative to our benchmark case [7]. Specifically, I first consider the joint impact of the new Basel III components and then study the impact of each new component separately by isolating it from the regulatory tools. As already mentioned above, the benchmark case I consider includes (Basel II, TR_{π} & Bailout). I measure the performance of each system in terms of the fragility of banks (BD) (measured as the average bank default rate), total credit volume (CV), total asset loss in the financial system ($AL = TotalSystemLiabilities - TotalSystemAssets$), output(Y) and unemployment (U). Results refer 300 Monte Carlos' simulation runs, each spanning 2400 time periods [8].

6.4.1 Basel III versus Basel II

In this section, I compare the performance of the Basel III regulatory framework relative to Basel II in terms of *BD,CV,AL,Y & U* over all possible combinations of the monetary and resolution policies. In the following paragraphs, I use the term "less conservative" monetary rules to denote a transition from a single to a dual or triple mandate monetary rule.

Bank defaults (BD) We find that transitioning to a less conservative monetary rule generally reduces bank defaults for both Basel regimes regardless of the resolution tool. However, we observe that Basel III does not always result in lower bank de-

[7] The parameters are consistent with those adopted by most national central banks and regulators, however, I have adjusted some of the parameters by a factor of 10^{-1} to be consistent with our model's timescale, unit of money and households' productivity

[8] A time period in our model typically corresponds to one month, hence a 2400 time period is 200 years. Hence it is reasonable to view the results of this work as the long-term performance of the system.

faults compared with Basel II. In particular, we find that Basel III results in more bank defaults than Basel II when the central bank uses an inflation targeting monetary rule but reduces the frequency of defaults as the monetary policy rule becomes less conservative irrespective of the adopted resolution tool. This stems from the fact that indexing the interest rate to only changes in inflation as in the TR_{π} monetary rule worsens the already tightening conditions on credit in Basel III's framework (see the following discussion on credit volume), which essentially triggers more downturns in the real sector since interest rates are not responding to the prevailing economic conditions in terms of unemployment and credit volume as in the dual & triple mandate monetary policies. The net effect of this would be an increase in the level of "loan write-offs" and thus increased probability of bankruptcy. Finally, we observe that a bailout resolution strategy results in the most frequent bank defaults while the lowest occurrence of bank defaults is achieved in a P&A regime. A possible explanation for this is the emergence of bigger banks that have absorbed other failed banks through a P&A. These banks have been shown to act essentially as stop gaps for bankruptcy cascades by Caccioli et al. (2011) and Gai et al. (2011). Another possibility is related to do way the cost of resolving failed banks is spread. Spreading the cost across all firms and households as in a bailout rather than a subset of the agents is more likely to plunge the economy into a recession thus triggering more bank defaults.

Credit volume (CV) The volume of allocated funds on the credit market is smaller in Basel III than Basel II for all combinations of resolution and monetary policies investigated due to greater credit tightening conditions stemming from the additional capital requirements in Basel III. Furthermore, we observe an upward trend in the volume of allocated credit in both Basel regimes and across all studied resolution mechanisms as the monetary policy becomes less conservative. This is so because the less conservative monetary rules increase the sensitivity of the interest rate to prevailing economic conditions which essentially reduces loan rationing across firms according to Equation 6.2. Moreover, we find that combining a bailout resolution with the triple mandate ($TR_{\pi,u,c}$) policy produces the best result. This

Table 6.3: Normalised bank default rates. Monetary rules: Single-mandate rule (TR_{π}), Dual-mandate rule ($TR_{\pi,u}$), Triple-mandate rule ($TR_{\pi,u,c}$). Basel III overlays: *CAR3* capital adequacy ratio, *CConB* capital conservation buffer, *CCyB* counter cyclical buffer, LR leverage requirement, *LCR* liquidity coverage ratio & *SIBs* capital surcharges for systemic important banks. **Less conservative monetary rule reduces bank defaults. Basel III does not always result in less bank defaults than Basel II. P&A regime results in the least bank defaults.** Standard errors are shown in parenthesis.

	Bailout			Bailin			P&A		
	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$
Basel II	1.0000	0.6249	0.4225	0.5468	0.3123	0.2113	0.1025	0.0572	0.0394
	(0.0237)	(0.0202)	(0.0153)	(0.0141)	(0.0112)	(0.0084)	(0.0013)	(0.0016)	(0.0013)
Basel III	1.0725	0.5577	0.3674	0.5862	0.2971	0.2017	0.1044	0.0574	0.0408
	(0.0217)	(0.0168)	(0.0130)	(0.0150)	(0.0101)	(0.0078)	(0.0012)	(0.0016)	(0.0014)

can easily be understood if one puts the preceding intuition together with the fact that firms are likely to request more loans in a bailout since they share directly in the burden of resolving failed banks.

Table 6.4: Normalised credit volume. Basel III results in less credit transactions than Basel II. Standard errors are shown in parenthesis.

	Bailout			Bailin			P&A		
	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$
Basel II	1.0000	1.1602	1.1606	0.9656	1.1459	1.1522	0.8497	1.1314	1.1503
	(0.0041)	(0.0031)	(0.0026)	(0.0038)	(0.0028)	(0.0026)	(0.0070)	(0.0040)	(0.0027)
Basel III	0.9564	1.1279	1.1343	0.9627	1.1354	1.1417	0.8345	1.1287	1.1477
	(0.0038)	(0.0027)	(0.0024)	(0.0035)	(0.0027)	(0.0025)	(0.0072)	(0.0039)	(0.0027)

Asset loss (AL) I measure the total asset loss as total systemic liabilities less total systemic assets. We find that the value of this loss reduces in both Basel configurations as the monetary policy becomes less conservative. This is most likely due to the fact that the loan demand from firms is higher since the interest rate is responding to the prevailing economic condition. The impact of this is twofold. First, it results in increased employment that ultimately translates to greater household wealth which increases consumption, thus reducing the likelihood of firm defaults which leads to lower "loan write-offs. Second, higher loan demand would lead to greater profitability for the banks, which would increase the asset side of their balance sheets. Furthermore, we observe that Basel III always outperforms Basel II except when a single mandate rule is used for the monetary policy. Finally, we find the P&A regime amplifies the magnitude of losses relative to the bail-in & bailout regime if combined with a single mandate rule. This stems from the fact that the P&A model may lead to severe disproportional interest payment structure for the healthy banks which may exacerbate losses if interest rates are not adjusted according to prevailing economic conditions.

Table 6.5: Normalised asset loss. P&A regime amplifies the magnitude of losses relative to the bail-in & bailout regime if combined with a single mandate rule. Standard errors are shown in parenthesis.

	Bailout			Bailin			P&A		
	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$
Basel II	1.0000	0.4245	0.5604	1.0657	0.3738	0.5291	1.1236	0.3206	0.4867
	(0.0055)	(0.0079)	(0.0088)	(0.0061)	(0.0089)	(0.0095)	(0.0063)	(0.0101)	(0.0109)
Basel III	1.0205	0.4085	0.5525	1.0718	0.3789	0.5233	1.1221	0.3178	0.4835
	(0.0056)	(0.0084)	(0.0091)	(0.0064)	(0.0090)	(0.0097)	(0.0062)	(0.0103)	(0.0109)

Output (Y) Basel III results in lower aggregate production output relative to Basel II for all combinations of monetary policies and resolution strategies I studied. This arises because of banks cutting lending to firms in a bid to comply with the additional capital overlays in Basel III framework, this in turn forces firms to revise their production plans downward. Also, we find that both Basel configuration respond negatively in terms of reduced output as the monetary policy becomes less conservative. Moreover, in addition to Klimek et al. (2015) who show that a P&A performs best when the economy is healthy (i.e. interest rates are low), I also observe a positive response in output as I move from a bailout to a P&A resolution regime regardless of the monetary policy used to set the interest rate. This can be understood if one considers the fact that in a bailout, the burden of resolving a failed bank is shared across firms and households which effectively slows down economic activity in terms of production and consumption. Furthermore, our result suggests that spreading the resolution cost across only banks as in a P&A may supersede the model of a bail-in which involves spreading the cost across banks and households' deposits [9].

Table 6.6: Normalised average output values across experiments. Basel III results in lower aggregate production output relative to Basel II for all combinations of monetary policies and resolution strategies. Standard errors are shown in parenthesis

	Bailout			Bailin			P&A		
	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$
Basel II	1.0000	0.9899	0.9860	1.0006	0.9903	0.9864	1.0003	0.9905	0.9866
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Basel III	0.9743	0.9846	0.9819	0.9951	0.9880	0.9845	0.9987	0.9894	0.9860
	(0.0025)	(0.0003)	(0.0003)	(0.0010)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)

Unemployment (U) We find that similar to the observations made for Y, the unemployment rate is higher in Basel III than in Basel II for all systemic combinations investigated since I use a linear Cobb-Douglas production function as in Equation 5.3. Also, the P&A resolution regime results in the least unemployment rate following the same intuition developed in the previous paragraph. Moreover, the $TR_{\pi,u}$ monetary rule seems to be only more effective than the TR_{π} rule in a bailout regime for Basel III but outperforms the $TR_{\pi,u,c}$ for both Basel configurations regardless of the resolution tool. This is so because responding to unemployment changes as in the $TR_{\pi,u}$ rule will stimulate the economy to recover faster since a bailout slows down economic activity due to the way the resolution burden is shared across board by all firms and households, however, controlling for credit volume at the same time as in the $TR_{\pi,u,c}$ rule is likely to be counterproductive since it is exactly in this period that

[9] Households' deposit accounts are affected whenever interbank loan write-offs are insufficient in meeting the resolution cost as I do not include deposit insurance in the model

lending conditions need to be loose. This result further strengthens recent calls for complex rules to be replaced by simpler regulation (Aikman et al. 2014; Haldane 2012)

Table 6.7: Normalised unemployment rates. Standard errors are shown in parenthesis. Bailout regime results in more unemployment than bail-in and P&A

	Bailout			Bailin			P&A		
	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$
Basel II	1.0000	2.0592	2.5533	0.9363	1.9954	2.4881	0.9708	1.9772	2.4658
	(0.0142)	(0.0139)	(0.0151)	(0.0130)	(0.0129)	(0.0148)	(0.0154)	(0.0134)	(0.0153)
Basel III	4.2854	2.6934	3.0353	1.5644	2.2725	2.7147	1.1331	2.1089	2.5447
	(0.3389)	(0.0432)	(0.0349)	(0.1365)	(0.0218)	(0.0222)	(0.0289)	(0.0180)	(0.0172)

6.4.2 Basel III components

In this section, I study the impact of each component of the Basel III framework including (*CAR3* capital adequacy ratio *CConB* capital conservation buffer, *CCyB* counter cyclical buffer, *LR* leverage requirement, *LCR* liquidity coverage ratio & *SIBs* capital surcharges for systemic important banks).

We find that the production volume from the system improves significantly by either eliminating the capital ratio requirement, conservation buffer or capital surcharges for SIBs in this order. This suggest that the reduction in GDP observed for Basel III in the previous section is mainly due to these additional capital overlay components. Furthermore, the impact of the Basel III components is generally more pronounced under a bailout regime especially the counter-cyclical buffer [10] since credit demand is higher in this regime (see the discussion in Section 6.4.1).

Although one would expect that eliminating either of the additional capital overlay components including *CAR3 & CConB* from the Basel III framework would exacerbate the frequency of bank defaults, I only found this to be true when the central bank uses the less conservative monetary policies and either a bail-in

[10]The counter-cyclical buffer is activated during periods of credit booms to help banks build a solid capital base during this period and correct the procyclicality in *CAR3*

or bailout resolution tool but not P&A. Moreover, the Basel III components do not appear to be addictive under a P&A regime. A possible explanation for this is that since the regime results in a decrease in the number of banks in the model, imposing additional regulatory constraints on the available banks would mostly serve to further reduce lending which may trigger economic recessions.

Table 6.8: Normalised credit volume. Standard errors are shown in parenthesis. *CAR3*, *CConB & SIBs* are the main components of Basel III. Leverage requirement (LR) has least impact.

	Bailout			Bailin			P&A		
	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$
Basel II	1.0000	1.1602	1.1606	0.9656	1.1459	1.1522	0.8497	1.1314	1.1503
	(0.0041)	(0.0031)	(0.0026)	(0.0038)	(0.0028)	(0.0026)	(0.0070)	(0.0040)	(0.0027)
Basel III	0.9564	1.1279	1.1343	0.9627	1.1354	1.1417	0.8345	1.1287	1.1477
	(0.0038)	(0.0027)	(0.0024)	(0.0035)	(0.0027)	(0.0025)	(0.0072)	(0.0039)	(0.0027)
Basel III − CAR3	0.9990	1.1505	1.1530	0.9650	1.1441	1.1481	0.8484	1.1320	1.1492
	(0.0041)	(0.0029)	(0.0026)	(0.0037)	(0.0028)	(0.0025)	(0.0072)	(0.0037)	(0.0026)
Basel III − CConB	0.9914	1.1452	1.1473	0.9655	1.1390	1.1467	0.8454	1.1275	1.1489
	(0.0041)	(0.0028)	(0.0024)	(0.0038)	(0.0028)	(0.0024)	(0.0071)	(0.0041)	(0.0026)
Basel III − LR	0.9566	1.1281	1.1349	0.9630	1.1353	1.1418	0.8355	1.1287	1.1477
	(0.0038)	(0.0027)	(0.0023)	(0.0034)	(0.0027)	(0.0025)	(0.0071)	(0.0039)	(0.0027)
Basel III − CCyB	0.9572	1.1266	1.1340	0.9639	1.1360	1.1427	0.8357	1.1295	1.1476
	(0.0039)	(0.0027)	(0.0024)	(0.0036)	(0.0027)	(0.0024)	(0.0071)	(0.0038)	(0.0027)
Basel III − SIBs	0.9705	1.1362	1.1411	0.9625	1.1369	1.1435	0.8440	1.1266	1.1489
	(0.0039)	(0.0027)	(0.0025)	(0.0037)	(0.0027)	(0.0024)	(0.0070)	(0.0042)	(0.0027)
Basel III − LCR	0.9556	1.1263	1.1336	0.9643	1.1345	1.1426	0.8411	1.1286	1.1469
	(0.0040)	(0.0027)	(0.0024)	(0.0035)	(0.0027)	(0.0024)	(0.0067)	(0.0037)	(0.0028)

Finally, eliminating the capital adequacy requirement results in the greatest increase in the volume of allocated credit. Also eliminating the additional conservation buffer and capital surcharges for SIBs appears to increase the credit volume. Nevertheless, isolating these components increases the volume of total systemic asset lost. The additional constraint on lending imposed by leverage requirement component does not seem to have any reasonable impact on the performance of the framework possibly owing to the fact that its impact is already masked by *CAR3*, *CConB*, *SIBs*.

6.5 Conclusion

The recent crisis exposed the inherent limitations of existing regulatory frameworks and precipitated calls for additional policy overlays to further improve the stability of the financial system and prevent a re-occurrence of the crisis. However, combining these policy instruments with the existing regulatory policies could contradict and conflict with the desired objective of the regulator and may even lead to unintended consequences. Addressing this challenge has become imperative to policy makers, who are left with no other choice but to base their decisions on common sense and anecdotal analogies to previous crisis (Farmer and Foley 2009).

In this work, I set out to investigate the long-term impact of the resolution tool used in resolving failed banks in the presence of monetary and macroprudential policies using an agent based model that couples the real economy and the financial system. In our model, the central bank follows a monetary rule that indexes interest rate relative to changes in economic conditions including inflation, inflation & unemployment, inflation, unemployment & credit volume by using a single, dual or triple mandate rule respectively. Further, I consider Basel II and Basel III regulatory frameworks as the possible macroprudential tools while bailout, bail-in and P&A (purchase & assumption) are the possible instruments available to the central bank for resolving failed banks, which only differ in the way the resolution cost is borne across the agents.

We find that Basel III does not necessarily result in less bank defaults relative to Basel II. Specifically, we find that Basel III produces more bank defaults if the central bank uses the single mandate monetary rule but reduces the frequency of defaults if the monetary policy rule also responds to changes in unemployment and credit volume. This stems from the fact that indexing the interest rate to only changes in inflation would be insufficient to stimulate the economy given the credit tightening conditions inherent in Basel III's framework. The net effect would most likely be increased economic recessions leading to increased probability of bank failures. Moreover, we find the emergence of a positive relationship between reduced bank defaults and asset loss and the transition to the dual and triple monetary rules. However, the dual monetary rule supersedes the triple rule in terms of unemployment during periods of production and consumption setbacks encountered in a bailout regime since controlling for credit volume in this period is likely to be counter-productive.

In addition, we find that the bailout regime results in the worst performance in terms of unemployment and output relative to a bail in and P&A owing to the fact that the resolution burden is shared across all firms and households implicitly slowing down production and consumption. Furthermore, we observe the least frequency of bank defaults under a P&A regime mostly due to the emergence of bigger and more stable banks that are better able to absorb losses from loan defaults. Finally, I investigated the contribution of each component included in the Basel III framework. We find that the capital adequacy ratio and conservation buffer components are the greatest contributor (i.e. *CAR3 & CConB*) to the observed characteristics of the Basel III framework. Furthermore, the Basel III components are not addictive under a P&A regime since this regime decreases the number of banks which further reinforces the reduction in lending already implied by the additional Basel III regulatory constraints on the available banks. Moreover, the additional constraint on lending imposed by leverage requirement component does not seem to have any reasonable impact on the performance of the framework possibly owing to the fact that its impact is already masked by *CAR3*, *CConB and SIBs (capital surcharges for systemic institutions).*

These analyses provide only a subset of the insights that can be gained on the interaction of regulatory policies using our approach. The model could be extended in several ways, for instance, I have focused only on insolvency for simplicity, however banks can also fail due to illiquidity. In fact, including this dynamic is likely to shed more light on the impact of the liquidity coverage ratio (LCR). Another possibility is to develop scenarios that allow the combination of a class of instruments, for instance studying the impact of a joint adoption of the bail-in and P&A resolution policies would be interesting.

Chapter 7

General Conclusion, Policy Recommendations and Future Work

The bitter experience of the recent global financial crisis exposed the inherent limitation of traditional policy models in characterising non-linear feedback and economic downturns associated with systemic financial risk. This thesis attempts to address these limitations by providing insights into the dynamics underlying emergence of financial crises and proposing effective regulatory policies to mitigate their causes and consequences. I do this under three major themes associated with systemic risk namely overlapping portfolios, risk diversification and policy interactions

In overlapping portfolios, I study the effect of power law distributions of degree and balance-sheet size on the stability of the system. I approach this by considering a model of financial contagion in a bipartite network of assets and banks recently introduced in the literature, Relative to the benchmark case of banks with homogeneous degrees and balance-sheet sizes, we find that if banks have a power-law degree distribution the system becomes less robust with respect to the initial failure of a random bank, and that targeted shocks to the most specialised banks (i.e. banks with low degrees) or biggest banks increases the probability of observing a cascade of defaults. In contrast, we find that a power-law degree distribution for assets increases stability with respect to random shocks, but not with respect to targeted shocks. I also study how allocations of capital buffers between banks affects the system's stability, and We find that assigning capital to banks in relation to their level of diversification reduces the probability of observing cascades of defaults relative to size based allocations. Finally, I propose a non-capital based policy that improves the resilience of the system by introducing disassortative mixing between banks and assets.

I then studied the consequences of diversification on financial stability and social welfare using an agent based model that couples the real economy and a financial system. I validate the model against its ability to reproduce several stylized facts reported in real economies. We find that the risk of an isolated bank failure (i.e. idiosyncratic risk) is decreasing with diversification. In contrast, the probability of joint failures (i.e. systemic risk) is increasing with diversification which results in more downturns in the real sector. We find that the system displays a ”robust yet fragile” behaviour particularly for low diversification. Moreover, I study the impact of introducing preferential attachment into the lending relationships between banks and firms. Finally, I show that a regulatory policy that promotes bank-firm credit transactions that reduce similarity between banks can improve financial stability whilst permitting diversification.

Lastly, I provide insights into the long term economic impact of different bank resolution instruments used by regulators to resolve a failed bank in the presence of prevailing monetary and macroprudential policies. I did this by considering Basel II and Basel III as the possible prudential frameworks; Bailout, Bailin, Purchase & Assumption(P&A) as the alternative resolution tools and single, dual and triple Taylor rules as the alternative monetary policy rules respectively targeting either one or more of changing economic conditions namely inflation, unemployment and credit volume. We find that Basel III does not always improve the stability of the financial system relative to Basel II. Specifically, we find that Basel III produces more bank defaults when the central bank follows an inflation targeting monetary rule but reduces the frequency of defaults if the monetary policy rule also responds to changes in unemployment and credit volume. Further, we observe that a bailout resolution strategy results in the most frequent bank defaults while the lowest occurrence of bank defaults is achieved in a P&A regime for all combinations of monetary and prudential policies. Also, I investigated the contribution of each Basel III component and find that the performance of Basel III framework is mainly characterised by the capital adequacy ratio and conservation buffer components while the additional constraint imposed by leverage requirement does not seem to have any reasonable impact on the performance of the framework. Moreover, the additional capital overlay Basel III components do not appear to be addictive under a P&A regime.

7.1 Policy Recommendations

In this section, I provide the following policy recommendations to mitigate systemic risk based on findings within the context of the research themes considered in this thesis.

1. A regulatory policy that assigns capital requirements to the most specialised banks performs better than random capital assignments when the network connectivity is high. However, focusing capital requirements on only the biggest bank does not appear to be effective relative to random assignments within the context of our model.

2. Diversification level is a more significant factor than size in building capital based policies especially as network connectivity increases.

3. A policy that promotes disassortative mixing (i.e. connecting the most specialised banks with the most concentrated assets) improves the resilience of the system without imposing additional capital requirements on banks.

4. Systemic risk build up can be controlled by using a policy that promotes bank-firm credit transactions that result in the smallest increase in the similarity between banks in the financial system.

5. Basel III is less beneficial than Basel II in relation to financial stability if the central bank uses the single mandate monetary rule but improves stability if the monetary policy rule also responds to changes in unemployment and credit volume.

6. In relation to resolving a failed financial institution, the bailout regime results in the worst performance in terms of unemployment and output relative to a bail-in and P&A.

7.2 Future Work: Retail Payment Systems

7.2.1 Bacs Payment Schemes Limited - A Case Study

Since its inception, over 100 billion transactions have been debited or credited to British bank accounts via Bacs. In 2013 over 5.7 billion UK payments were made this way with a total value of almost £4.2 trillion (*UK Payment Markets - Summary*). Over 3.5 billion Direct Debit payments are processed by Bacs a year and 80 per cent of British adults have at least one Direct Debit commitment. Nearly 90 per cent of the UK workforce is paid via Bacs Direct Credit, while it is also the payment method of choice for a range of other applications such as pension payments, employee expenses, insurance settlements, dividends and refunds. In 2013 more than 2.14 billion payments were processed using Bacs Direct Credit. Thus, it is imperative to study these payment networks for the ultimate benefit of businesses and consumers.

7.2.1.1 Research Questions

1. Network topology study, Stress testing and What-if scenario analysis: The intention here is to analyse and describe the Bacs direct credit and direct debit payment network using established network measures as done for the Mexican payment network. This would give us insight in the global and individual node characteristics of the payment network. In addition, I intend to study the effect of random and probable shocks to the system's dynamics. A common scenario analysis would be the case when a randomly selected node is unable to fulfil its payment obligation due to operational difficulties - it will be interesting to look at the effect this kind of scenario would have on the system.

2. Identify risk outliers arising from within the direct credit and direct debit payment schemes: Here, I am concerned with possible operational and credit risk

that undermine both schemes along with their associated cost to consumers, businesses and banks. Our aim here is to propose measures which when implemented can mitigate these risks along with the cost involved. Thereby providing incentives for the further adoption of both schemes.

3. Study the overall impact of Bacs direct credit and direct debit payment schemes on UK economic growth: I am interested in studying the correlation between the adoption of both schemes and macroeconomic indicators like GDP, employment etc. Our aim is to provide evidence for the relevant of both schemes to the UK economy built on sound statistical analysis.

4. Provide evidence of the cost associated with cross ownership concerns between payment schemes and infrastructural Providers: I note that most payment schemes are owned and controlled by the banks who also are the main users of the services and as such have an incentive to minimise cost. However, this has led to a degree of inertia regarding competition and the pace of innovation, thereby limiting the options available to the scheme in selecting infrastructural suppliers. Our aim here is to provide countercyclical suggestions to resolve this challenge.

5. Study the optimal access fee structure and competition strategy for the Direct debit and Bacs Direct Credit Payment Platform using lessons learned from the two-sided market theory: While it can be argued that the direct debit and Bacs direct credit product schemes do not necessarily fit the description of a traditional two-sided market, our aim here is to remodel the existing theory to capture peculiarities of the Bacs payment platform. This would enable us to determine the optimal access fee structure and competition strategy necessary to increase the transaction volume and revenue from the Bacs platform.

Appendix A

Appendix: Chapter 5

Table A.1: Normalised bank default rates across experiments. Monetary policies: single-mandate rule TR_{π}, dual-mandate rule $TR_{\pi,u}$ & triple-mandate rule $TR_{\pi,u,c}$. Basel III overlays: *CAR3* capital adequacy ratio, *CConB* capital conservation buffer, *CCyB* counter cyclical buffer, LR leverage requirement, *LCR* liquidity coverage ratio & *SIBs* capital surcharges for systemic important banks. **Standard errors are shown in parenthesis**

	Bailout			Bailin			P&A		
	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$
Basel II	1.0000	0.6249	0.4225	0.5468	0.3123	0.2113	0.1025	0.0572	0.0394
	(0.0237)	(0.0202)	(0.0153)	(0.0141)	(0.0112)	(0.0084)	(0.0013)	(0.0016)	(0.0013)
Basel III	1.0725	0.5577	0.3674	0.5862	0.2971	0.2017	0.1044	0.0574	0.0408
	(0.0217)	(0.0168)	(0.0130)	(0.0150)	(0.0101)	(0.0078)	(0.0012)	(0.0016)	(0.0014)
$Basel\ III-CAR3$	1.0239	0.5969	0.3994	0.5636	0.3167	0.2064	0.1023	0.0559	0.0393
	(0.0249)	(0.0183)	(0.0144)	(0.0142)	(0.0120)	(0.0081)	(0.0013)	(0.0016)	(0.0013)
$Basel\ III-CConB$	1.0516	0.5849	0.3868	0.5708	0.3040	0.1986	0.1022	0.0568	0.0399
	(0.0238)	(0.0184)	(0.0134)	(0.0145)	(0.0109)	(0.0075)	(0.0013)	(0.0016)	(0.0014)
$Basel\ III-LR$	1.0693	0.5576	0.3671	0.5862	0.2972	0.2017	0.1042	0.0574	0.0408
	(0.0217)	(0.0168)	(0.0131)	(0.0149)	(0.0101)	(0.0078)	(0.0012)	(0.0016)	(0.0014)
$Basel\ III-CCyB$	1.0809	0.5571	0.3680	0.5895	0.2988	0.2016	0.1042	0.0574	0.0408
	(0.0228)	(0.0172)	(0.0128)	(0.0153)	(0.0103)	(0.0077)	(0.0012)	(0.0016)	(0.0014)
$Basel\ III-SIBs$	1.0439	0.5547	0.3800	0.5923	0.3044	0.1996	0.1029	0.0570	0.0398
	(0.0218)	(0.0162)	(0.0135)	(0.0159)	(0.0105)	(0.0078)	(0.0013)	(0.0017)	(0.0013)
$Basel\ III-LCR$	1.0640	0.5577	0.3682	0.5914	0.2966	0.2008	0.1035	0.0574	0.0408
	(0.0221)	(0.0170)	(0.0132)	(0.0149)	(0.0101)	(0.0079)	(0.0012)	(0.0016)	(0.0014)

Table A.2: Normalised average credit volume granted across experiments.

	Bailout			Bailin			P&A		
	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$
Basel II	1.0000	1.1602	1.1606	0.9656	1.1459	1.1522	0.8497	1.1314	1.1503
	(0.0041)	(0.0031)	(0.0026)	(0.0038)	(0.0028)	(0.0026)	(0.0070)	(0.0040)	(0.0027)
Basel III	0.9564	1.1279	1.1343	0.9627	1.1354	1.1417	0.8345	1.1287	1.1477
	(0.0038)	(0.0027)	(0.0024)	(0.0035)	(0.0027)	(0.0025)	(0.0072)	(0.0039)	(0.0027)
$Basel\ III - CAR3$	0.9990	1.1505	1.1530	0.9650	1.1441	1.1481	0.8484	1.1320	1.1492
	(0.0041)	(0.0029)	(0.0026)	(0.0037)	(0.0028)	(0.0025)	(0.0072)	(0.0037)	(0.0026)
$Basel\ III - CConB$	0.9914	1.1452	1.1473	0.9655	1.1390	1.1467	0.8454	1.1275	1.1489
	(0.0041)	(0.0028)	(0.0024)	(0.0038)	(0.0028)	(0.0024)	(0.0071)	(0.0041)	(0.0026)
$Basel\ III - LR$	0.9566	1.1281	1.1349	0.9630	1.1353	1.1418	0.8355	1.1287	1.1477
	(0.0038)	(0.0027)	(0.0023)	(0.0034)	(0.0027)	(0.0025)	(0.0071)	(0.0039)	(0.0027)
$Basel\ III - CCyB$	0.9572	1.1266	1.1340	0.9639	1.1360	1.1427	0.8357	1.1295	1.1476
	(0.0039)	(0.0027)	(0.0024)	(0.0036)	(0.0027)	(0.0024)	(0.0071)	(0.0038)	(0.0027)
$Basel\ III - SIBs$	0.9705	1.1362	1.1411	0.9625	1.1369	1.1435	0.8440	1.1266	1.1489
	(0.0039)	(0.0027)	(0.0025)	(0.0037)	(0.0027)	(0.0024)	(0.0070)	(0.0042)	(0.0027)
$Basel\ III - LCR$	0.9556	1.1263	1.1336	0.9643	1.1345	1.1426	0.8411	1.1286	1.1469
	(0.0040)	(0.0027)	(0.0024)	(0.0035)	(0.0027)	(0.0024)	(0.0067)	(0.0037)	(0.0028)

Table A.3: Normalised mean asset loss across simulations.

	Bailout			Bailin			P&A		
	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$
Basel II	1.0000	0.4245	0.5604	1.0657	0.3738	0.5291	1.1236	0.3206	0.4867
	(0.0055)	(0.0079)	(0.0088)	(0.0061)	(0.0089)	(0.0095)	(0.0063)	(0.0101)	(0.0109)
Basel III	1.0205	0.4085	0.5525	1.0718	0.3789	0.5233	1.1221	0.3178	0.4835
	(0.0056)	(0.0084)	(0.0091)	(0.0064)	(0.0090)	(0.0097)	(0.0062)	(0.0103)	(0.0109)
$Basel\ III - CAR3$	1.0090	0.4128	0.5564	1.0712	0.3726	0.5267	1.1272	0.3212	0.4857
	(0.0055)	(0.0080)	(0.0088)	(0.0059)	(0.0091)	(0.0095)	(0.0063)	(0.0102)	(0.0110)
$Basel\ III - CConB$	1.0099	0.4148	0.5562	1.0709	0.3775	0.5271	1.1288	0.3217	0.4858
	(0.0058)	(0.0082)	(0.0089)	(0.0062)	(0.0090)	(0.0094)	(0.0062)	(0.0103)	(0.0109)
$Basel\ III - LR$	1.0203	0.4083	0.5526	1.0716	0.3789	0.5236	1.1221	0.3178	0.4835
	(0.0056)	(0.0084)	(0.0091)	(0.0064)	(0.0090)	(0.0097)	(0.0062)	(0.0103)	(0.0109)
$Basel\ III - CCyB$	1.0223	0.4043	0.5520	1.0725	0.3789	0.5238	1.1223	0.3174	0.4837
	(0.0057)	(0.0086)	(0.0090)	(0.0064)	(0.0091)	(0.0097)	(0.0062)	(0.0104)	(0.0109)
$Basel\ III - SIBs$	1.0132	0.4114	0.5534	1.0735	0.3767	0.5252	1.1254	0.3192	0.4881
	(0.0060)	(0.0082)	(0.0090)	(0.0061)	(0.0091)	(0.0096)	(0.0063)	(0.0104)	(0.0107)
$Basel\ III - LCR$	1.0180	0.4065	0.5529	1.0710	0.3782	0.5253	1.1243	0.3175	0.4843
	(0.0058)	(0.0085)	(0.0090)	(0.0064)	(0.0090)	(0.0096)	(0.0063)	(0.0103)	(0.0108)

Table A.4: Normalised average output values across experiments.

	Bailout			Bailin			P&A		
	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$
Basel II	1.0000	0.9899	0.9860	1.0006	0.9903	0.9864	1.0003	0.9905	0.9866
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Basel III	0.9743	0.9846	0.9819	0.9951	0.9880	0.9845	0.9987	0.9894	0.9860
	(0.0025)	(0.0003)	(0.0003)	(0.0010)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
$Basel\ III - CAR3$	0.9991	0.9889	0.9851	1.0003	0.9898	0.9861	0.9999	0.9905	0.9866
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
$Basel\ III - CConB$	0.9953	0.9876	0.9841	0.9993	0.9893	0.9855	0.9996	0.9901	0.9864
	(0.0010)	(0.0002)	(0.0002)	(0.0004)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
$Basel\ III - LR$	0.9742	0.9846	0.9820	0.9951	0.9880	0.9845	0.9987	0.9894	0.9860
	(0.0025)	(0.0003)	(0.0003)	(0.0010)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
$Basel\ III - CCyB$	0.9734	0.9839	0.9819	0.9957	0.9881	0.9846	0.9990	0.9895	0.9860
	(0.0025)	(0.0004)	(0.0003)	(0.0010)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
$Basel\ III - SIBs$	0.9817	0.9862	0.9831	0.9964	0.9885	0.9855	0.9993	0.9900	0.9862
	(0.0022)	(0.0003)	(0.0004)	(0.0009)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
$Basel\ III - LCR$	0.9723	0.9842	0.9817	0.9948	0.9879	0.9845	0.9983	0.9895	0.9860
	(0.0027)	(0.0004)	(0.0003)	(0.0011)	(0.0002)	(0.0002)	(0.0003)	(0.0001)	(0.0001)

Table A.5: Normalised unemployment rates across experiments.

	Bailout			Bailin			P&A		
	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$	TR_{π}	$TR_{\pi,u}$	$TR_{\pi,u,c}$
Basel II	1.0000	2.0592	2.5533	0.9363	1.9954	2.4881	0.9708	1.9772	2.4658
	(0.0142)	(0.0139)	(0.0151)	(0.0130)	(0.0129)	(0.0148)	(0.0154)	(0.0134)	(0.0153)
Basel III	4.2854	2.6934	3.0353	1.5644	2.2725	2.7147	1.1331	2.1089	2.5447
	(0.3389)	(0.0432)	(0.0349)	(0.1365)	(0.0218)	(0.0222)	(0.0289)	(0.0180)	(0.0172)
$Basel\ III - CAR3$	1.0844	2.1687	2.6552	0.9588	2.0570	2.5260	0.9993	1.9769	2.4700
	(0.0228)	(0.0158)	(0.0184)	(0.0142)	(0.0134)	(0.0150)	(0.0182)	(0.0134)	(0.0151)
$Basel\ III - CConB$	1.5437	2.3303	2.7762	1.0537	2.1125	2.6017	1.0297	2.0284	2.4899
	(0.1386)	(0.0208)	(0.0216)	(0.0485)	(0.0164)	(0.0169)	(0.0195)	(0.0150)	(0.0148)
$Basel\ III - LR$	4.2999	2.6970	3.0251	1.5662	2.2722	2.7144	1.1327	2.1089	2.5447
	(0.3404)	(0.0431)	(0.0336)	(0.1363)	(0.0219)	(0.0222)	(0.0289)	(0.0180)	(0.0172)
$Basel\ III - CCyB$	4.4012	2.7777	3.0407	1.4846	2.2568	2.7018	1.0981	2.1050	2.5431
	(0.3333)	(0.0551)	(0.0360)	(0.1394)	(0.0206)	(0.0209)	(0.0233)	(0.0173)	(0.0170)
$Basel\ III - SIBs$	3.3169	2.5028	2.9004	1.4167	2.2059	2.6001	1.0674	2.0432	2.5171
	(0.2901)	(0.0432)	(0.0513)	(0.1182)	(0.0224)	(0.0175)	(0.0231)	(0.0165)	(0.0168)
$Basel\ III - LCR$	4.5631	2.7413	3.0643	1.6020	2.2842	2.7135	1.1834	2.1040	2.5475
	(0.3554)	(0.0561)	(0.0379)	(0.1507)	(0.0238)	(0.0213)	(0.0398)	(0.0182)	(0.0175)

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