The Emergence of Interbank Exposure Networks:

An Empirical Analysis and Game Theoretical Models

Jens Krause

Pembroke College
University of Oxford

A thesis submitted for the degree of
Doctor of Philosophy

Michaelmas 2015

The Emergence of Interbank Exposure Networks:
An Empirical Analysis and Game Theoretical Models

Jens Krause

Pembroke College
University of Oxford

A thesis submitted for the degree of
Doctor of Philosophy

Michaelmas 2015

This thesis studies the emergence of financial exposures between banks and introduces a novel game of financial network formation. It shows empirically that governance structures influence how banks use the interbank market to manage liquidity and that strategic factors are additional drivers of interbank lending for private banks (Ch. 2). It further develops a model of optimal bank behaviour in the absence of liquidity shocks considering the effect of an exogenous bailout probability (Ch. 3), and introduces a model of endogenous liquidity co-insurance formation (Ch. 4).

The first chapter, *The Purpose of Interbank Markets*, tests competing theories of interbank lending using 43 quarters (2002-2012) of confidential data on the German banking sector and interbank market. It shows that banks use the interbank market for liquidity co-insurance as traditionally assumed. However, the importance of the liquidity management function is higher for regionally-focused credit cooperatives and savings banks than for private commercial banks. A distinct effect for private banks is identified; for private banks, increases in interbank liabilities are shown to correlate with a proxy for the bailout probability of banks. The chapter thus offers empirical support for an emerging literature on strategic behaviour in interbank markets and highlights the need to extend the traditional model of liquidity co-insurance.

The second chapter, *The Emergence of Interbank Exposures*, develops a model showing that, even in the hypothetical absence of liquidity shocks, under some conditions the presence of conditional liability guarantees can lead to interbank exposures as an equilibrium outcome. It shows that such an equilibrium is characterised by banks of different sizes and asymmetric bank behaviour. Some banks are active only as lenders with others investing in a productive technology while borrowing in the interbank market. An equilibrium interbank rate is derived which depends on parameters characterising the bailout probability, including different parameters of government behaviour.

The third chapter, *Coordination and Competition in the Formation of Financial Networks*, introduces a generalisation and extension of the seminal work of Allen and Gale (2000). It studies liquidity co-insurance between deposit-taking banks in an n-region economy. Both a static and a dynamic model of the endogenous formation of interbank liquidity co-insurance links are examined. Using a novel approach to model liquidity co-insurance, it is shown that contrary to previous findings it is not possible for banks with limited information to insure optimally against liquidity shocks. However, in a dynamic formulation of the model with best-response dynamics and learning, socially optimal insurance is an evolutionary stable equilibrium. The chapter also studies an extension to the model that introduces non-zero bailout probabilities, which endogenously leads to interbank networks consistent with the structure of interbank exposure networks documented empirically.

The Emergence of Interbank Exposure Networks:
An Empirical Analysis and Game Theoretical Models

To my parents and sister

Contents

Acknowledgements

To my parents Detlev and Ulrike, I am indebted to you for your lifelong, unfailing support, guidance, and love. To my sister Jana, thank you for your friendship and encouragement. This thesis is dedicated to the three of you. I am further deeply indebted to my supervisors Felix Reed-Tsochas and H. Peyton Young, who both are a source of inspiration and shaped my thinking through their writings and our discussions. To Felix, thank you for your friendship and especially for the encouragement to pursue this line of research.

My work has benefited from critical discussions and comments by many including Christoph Aymanns, Marcel Bluhm, Ben Craig, Andrew Elliott, Daniel Fricke, Doyne Farmer, Alysia Garmulewicz, Co-Pierre Georg, Austin Gerig, Akshay Kotak, Jan R. Magnus, Christoph Memmel, Alan Morrison, Benjamin Munyan, Thomas Noe, Pascal Paul, Tarik Roukny, Nicholas Sabin, Nir Vulkan, and an anonymous referee. I am grateful for all my family, friends, and colleagues in Oxford and elsewhere who have supported this project and have been an encouragement and inspiration throughout. To Nicola, thank you for your companionship and love, your work and being in the world are a unique source of inspiration and joy.

I am grateful to the Konrad-Adenauer-Foundation for financial and institutional support, both ongoing and received through the doctoral scholarship program (Promotionsförderung) between October 2011 and September 2014. I thank the Deutsche Bundesbank for financial and institutional support received as a guest researcher between 2012 and 2015. I thank the BT Centre for Major Programme Management for financial support during my first year as a doctoral student (October 2010 - September 2011). I am further grateful to the The Institute for New Economic Thinking at the Oxford Martin School, Pembroke College, and the Saïd Business School for financial support at various stages of the DPhil. The views stated in this work are my own and do not necessarily reflect those of the Deutsche Bundesbank or its staff, or of any other institution supporting this work. Lastly, I am grateful for the CABDyN Complexity Centre, the Saïd Business School, Pembroke College, Magdalen College, and the University of Oxford for the community and offering platforms for learning, stimulating exchange, and lasting friendships.

Abstract

This thesis studies the emergence of financial exposures between banks and introduces a novel game of financial network formation. It shows empirically that governance structures influence how banks use the interbank market to manage liquidity and that strategic factors are additional drivers of interbank lending for private banks (Ch. 2). It further develops a model of optimal bank behaviour in the absence of liquidity shocks considering the effect of an exogenous bailout probability (Ch. 3), and introduces a model of endogenous liquidity co-insurance formation (Ch. 4).

The first chapter, *The Purpose of Interbank Markets*, tests competing theories of interbank lending using 43 quarters (2002-2012) of confidential data on the German banking sector and interbank market. It shows that banks use the interbank market for liquidity co-insurance as traditionally assumed. However, the importance of the liquidity management function is higher for regionally-focused credit cooperatives and savings banks than for private commercial banks. A distinct effect for private banks is identified; for private banks, increases in interbank liabilities are shown to correlate with a proxy for the bailout probability of banks. The chapter thus offers empirical support for an emerging literature on strategic behaviour in interbank markets and highlights the need to extend the traditional model of liquidity co-insurance.

The second chapter, *The Emergence of Interbank Exposures*, develops a model showing that, even in the hypothetical absence of liquidity shocks, under some conditions the presence of conditional liability guarantees can lead to interbank exposures as an equilibrium outcome. It shows that such an equilibrium is characterised by banks of different sizes and asymmetric bank behaviour. Some banks are active only as lenders with others investing in a productive technology while borrowing in the interbank market. An equilibrium interbank rate is derived which depends on parameters characterising the bailout probability, including different parameters of government behaviour.

The third chapter, *Coordination and Competition in the Formation of Financial Networks*, introduces a generalisation and extension of the seminal work of Allen and Gale (2000). It studies liquidity co-insurance between deposit-taking banks in an n-region economy. Both a static and a dynamic model of the endogenous formation of interbank liquidity co-insurance links are examined. Using a novel approach to model liquidity co-insurance, it is shown that contrary to previous findings it is not possible for banks with limited information to insure optimally against liquidity shocks. However, in a dynamic formulation of the model with best-response dynamics and learning, socially optimal insurance is an evolutionary stable equilibrium. The chapter also studies an extension to the model that introduces non-zero bailout probabilities, which endogenously leads to interbank networks consistent with the structure of interbank exposure networks documented empirically.

List of Figures

List of Tables

Chapter 1

Introduction

This thesis examines the emergence of financial exposures between banks and proposes a new model of financial network formation. In three self-contained chapters we study the emergence of liability exposures between banks. We show that the traditional model of interbank markets as a mechanism for liquidity co-insurance, which is the predominant modelling assumption since the seminal work of Allen and Gale (2000), offers only a partial account of the drivers of interbank exposures. An empirical study of the German banking sector and interbank market (Chapter 2) shows that interbank markets can serve a variety of purposes, in the sense that changes in interbank lending correlate with a variety of drivers. The empirical results further reveal an interesting link between the governance structure of banks and their activities in the interbank market. These findings motivate two theoretical models of mechanisms that can generate interbank exposures.

The first model (Chapter 3) proposes a mechanism through which banks would enter lending relationships even if no risk of unanticipated liquidity needs existed. We specify the conditions under which banks find it optimal to enter interbank liabilities in the presence of uncertain liability guarantees by a third party, such as governmentfunded bailouts. Based both on the empirical findings and the theoretical results we introduce a model of endogenous network formation (Chapter 4). We propose a novel way to study liquidity co-insurance between banks that takes into account the liquidity management function of interbank markets but also allows the inclusion of alternative drivers. While each chapter can be read independently, they draw on and motivate each other.

The views stated in this work, specifically in Chapter 2 *The Purpose of Interbank Markets*, are my own and do not necessarily reflect those of the Deutsche Bundesbank or its staff, or those of any other institution supporting this work. Moreover, throughout the thesis the pronoun 'we' is used. This is purely a stylistic choice, all work is my own. In the technical sections of the three main chapters we try to be consistent in the use of variables and symbols. Nonetheless, the different models refer to and build on established models in the literature that do not always align. While within each chapter symbols are used consistently and are uniquely defined, this is not always the case between chapters.

In the remainder of the introduction we first provide an overarching motivation for the work in the three main chapters. We then position each chapter with regards to the existing relevant literature and outline the individual contributions. Following the three chapters is a discussion of the work including implications for policy makers, central banks, and scholars.

1.1 Motivation

This thesis is a child of the immediate aftermath of the global financial turmoil of 2007-2009, which saw a global financial crisis originating in the United States but spreading globally due to liabilities between financial institutions and due to common asset holdings of investors (Brunnermeier, 2009). It saw failures of large banking institutions such as Lehman Brothers, but also saw selective government bailouts of banks globally, including amongst others giants such as Barclays, HSBC, and the Royal Bank of Scotland in the United Kingdom, as well as the Bank of America and the Citigroup in the United States. The crisis extended to sovereign debt restructuring in Greece and Iceland as well as major political disruptions brought on by attempts of governments to bail out banking sectors and provide liquidity to their ailing economies.

It is well known that asset (price) bubbles and their resolution, financial crises, are an integral part of free market economies in which prices and market participants interact freely (Abreu and Brunnermeier, 2003; Carmen and Rogoff, 2014; Shiller, 2015). Price bubbles have been recurring for centuries. Nonetheless, over the past five decades alone cross-border exposures between financial institutions have increased significantly (Minoiu and Reyes, 2013). Many arguments have been put forward that in financial systems, similar to what has been found in network models of eco-systems (May, 1973), the presence of complex patterns of co-exposures or co-dependencies can make systems vulnerable even to relatively small perturbations (Battiston et al., 2012*a*; Haldane and May, 2011; May, Levin and Sugihara, 2008; May, 2013; Saavedra et al., 2014; Smerlak et al., 2015; Schweitzer et al., 2009; Zawadowski, 2013). It has been shown that in highly interconnected financial systems even small changes in asset prices or macroeconomic shocks can lead to systemic crises, which often manifest themselves as a dry-up of liquidity (Anand et al., 2013; Acharya, Gale and Yorulmazer, 2011; Bolton, Santos and Scheinkman, 2011; Diamond and Rajan, 2005). The drying up of liquidity in financial markets has been identified as one of the main drivers of the global financial crisis (Anand, Gai and Marsili, 2012; Brunnermeier, 2009). Liquidity dry-ups not only impact the financial sector but also the real economy because banks no longer fulfil their role as financial intermediaries providing funding for projects from short-term fluctuating demand deposits (Diamond and Dybvig, 1983; Diamond, 1984).

Thus, while asset bubbles and crises are an integral part of financial systems, the consequences of shocks to the liquidity supply can vary depending on the structure of the financial system they affect. Contagious failures, i.e. defaults of financial institutions as a consequence of an interconnected financial system (Allen and Gale, 2000), have been studied extensively under what may be labelled research into systemic risk. Early works in this area include Allen and Gale (1998), Cifuentes, Ferrucci and Shin (2005), Diamond and Dybvig (1983), Eisenberg and Noe (2001), Freixas and Parigi (1998), Freixas, Parigi and Rochet (2000), and Rochet and Tirole (1996). Several recent works provide a good overview of the field and an introduction to the relevant models (e.g. Bisias et al., 2012; Brunnermeier and Oehmke, 2013; Gai, 2013).

Since the seminal work of Allen and Gale (2000) and Eisenberg and Noe (2001) systemic risk has been studied as a function of networked financial systems. Results vary with regard to when the structure of networks facilitates or hinders the transmission of contagious shocks (cf. Acemoglu, Ozdaglar and Tahbaz-Salehi, 2015; Glasserman and Young, 2015; or Nier et al., 2007). Most theoretical work suggests that both the connectivity of financial systems as well as the size of the shock to the systems matter. They matter in the sense that under some combination of connectivity and shock type a specific structure may be more resilient and absorb shocks, while under another shock type the same structure may exacerbate shocks and have contagious consequences. This property has become known as the ‘robust-yet-fragile’ property of financial systems (Gai, 2013). Glasserman and Young (2015) provide some bounds on these effects relating shock distributions to bank balance sheets as well as interbank co-exposures. Hüser (2015) provides a comprehensive overview of the literature on the role of network structure for systemic risk and Gai (2013) an introduction to the current debates in systemic risk research.

In addition to research into the link between the structure of financial co-exposures and systemic risk, an important research programme has examined the policy responses appropriate to dealing with fluctuations in liquidity supply. Some central works in this area include Acharya and Yorulmazer (2007), Acharya, Gromb and Yorulmazer (2012), Cordella and Yeyati (2003), Holmström and Tirole (1998), Diamond and Rajan (2005), Freixas et al. (2000), Freixas, Rochet and Parigi (2004), Freixas and Rochet (2008), and Freixas, Martin and Skeie (2011). The central question in this line of research is whether a lender of last resort should intervene in private liquidity supply, when to intervene, and in what form to intervene. We will discuss some of these works in more detail in Chapter 5, but policy makers and central banks face one central tradeoff. When liquidity is sparse, actions to supply markets with liquidity will protect depositors and benefit the real economy. At the same time, bailouts and lower interest rates pose a moral hazard for banks (Allen, 2001). In the presence of a lender of last resort profit-maximising banks have an incentive to increase lending and borrowing at lower interest rates, which leads to increased co-exposures and thus to an increased potential of contagious effects. The challenges accompanying 'Too-Big-To-Fail' institutions are often argued to be a consequence of such policies (Davies and Tracey, 2014; Freixas, Parigi and Rochet, 2000). Shapiro and Skeie (2015) provide a recent discussion on the effect of market incentives on bank governance.

In summary, asset bubbles and their corrections cannot be avoided and are part of a free market economy. Systemic risk arises when the structure of financial networks themselves exacerbate the effects of price corrections or other liquidity shocks, and losses and defaults spread by contagion between financial institutions. A lender of last resort and macroeconomic policies can create incentives for financial institutions to enter a sub-optimal amount of exposure relationships, which can create systemic risk and liquidity crises. So, in the presence of any sort of potential intervention in the markets for liquidity provision, private insurance mechanisms may be distorted and the cause for the need of intervention intensified rather than neutralised.

Of course there are many reasons for why financial institutions should enter bilateral liability relationships. These include financial intermediation (Diamond, 1984; Farboodi, 2014; Gale and Kariv, 2007) and insurance against liquidity shocks (Allen and Gale, 2000; Brusco and Castiglionesi, 2007; Freixas, Parigi and Rochet, 2000). Even in the presence of a lender of last resort, banks would need to self-insure most of the time. Such insurance requires coordination in a setting with incomplete information and competing entities. It is precisely in this domain where we seek to make a contribution. Rather than taking the structure of financial networks as given and analysing their systemic risk potential, we focus on their formation and evolution. What strikes us as interesting in this line of research is the interplay of competition and coordination between self-interested actors that bring about financial networks. This interaction happens in the presence of uncertain interventions by policy makers and the lender of last resort, where the interventions vary depending on to the structure of the financial system and the interventions in turn influence the evolution of the structure itself.

The main area of contribution of this thesis thus lies at the intersection of furthering our understanding of drivers of interbank lending, and studying the endogenous emergence of interbank exposures in the light of potential regulatory interventions. In this sense our work builds on two extensive research traditions. The first is the evolution of cooperation between self-interested actors and the second studying networks both as an outcome of strategic games as well as studying coordination games in network contexts. The formal definition of the question of whether cooperation can emerge between self-interested actors goes back at least to the work of Hardin (1968) and Rapoport and Chammah (1965). Axelrod and Hamilton (1981), and Axelrod (1984) showed that no central authority is necessary for cooperation to emerge. The theoretical puzzle of the circumstances under which altruistic actions and cooperation can be maintained is the subject of a vast research programme in the social sciences, evolutionary biology, physics, and computer science of which Bowles and Gintis (2008) provide a good overview. This tradition, while not central to the empirical work, provides an important motivation for the theoretical models.

It has been shown both theoretically and experimentally that high degrees of cooperation are not a trivial outcome (Bendor and Swistak, 1997; Boyd and Lorberbaum, 1987; Dal Bó and Fréchette, 2011; Fehr and Fischbacher, 2003; Fischbacher, Gächter and Fehr, 2001) and that most people are conditional cooperators (Fischbacher, Gächter and Fehr, 2001; Gracia-Lázaro et al., 2012; Grujić et al., 2010). Of the mechanisms that have been identified to enable cooperation, several forms of reciprocity, i.e. the ability to reciprocate cooperative behaviour and punish exploitive behaviour, are the most important (Axelrod and Dion, 1988; Axelrod, 1981; Nowak, 2006*b*; West, El Mouden and Gardner, 2011). Axelrod has famously introduced 'Tit-For-Tat (TFT)' as the winning strategy for a repeated prisoner's dilemma game.[1] While in evolutionary biology altruistic behaviour is often explained by ge-

---

[1] When noise is introduced to the model, i.e. errors or other exogenous shocks are possible, TFT is not optimal and 'nicer' strategies aggregate higher payoffs (Bendor, 1993; Bendor, Kramer and

netic relatedness (Hamilton, 1963), reciprocity and its enforcement through reward or punishment appears to be the most important mechanism in socio-economic systems (Binmore, 1998; Boyd and Richerson, 1988; Sugden, 1984).

Reciprocity requires certain social or physical structural conditions. In order to reciprocate behaviour, individuals must know the behaviour of others or interact with them repeatedly (Axelrod, 1984). For instance, it is shown that for most mechanisms of reciprocity a form of coordinated punishment of free-riders is necessary to maintain cooperation (Boyd, Gintins and Bowles, 2010). While other mechanisms have been proposed such as indirect reciprocity through image scoring (Nowak and Sigmund, 1998), which have been extended to include imitation and trust-based mechanisms (Saavedra, Smith and Reed-Tsochas, 2010), social structure needs to be taken into account when studying cooperation. It is well understood in economics and the social sciences that strategic behaviour of agents is influenced by the environments they are embedded in (Granovetter, 1985). In game theory, games on graphs have been used extensively to model the influence of social and physical structure on the strategic behaviour of agents. Such models include Axelrod (1984), Economides (1996), Ellison (1993), Jackson and Yariv (2007), Kearns, Littman and Singh (2001), May, Bohoeffer and Nowak (1995). Nowak (2006*a*) provides an overview from the perspective of evolutionary game theory.[2]

When studying the evolution of private liquidity co-insurance that is often assumed in the models following Allen and Gale (2000), banks essentially face challenges of cooperation. Private insurance has positive externalities and requires coordination to work reliably, but it is not strictly speaking an altruistic act. However, if insur-

---

Swistak, 1996; Nowak and Sigmund, 1992; Nowak, Bonhoeffer and May, 1994).

[2] Other important work in this area include Binmore and Samuelson (1994); Foster and Young (1990); Gintis (2000); Samuelson (1998); Skyrms (1996); Young (1998); Weibull (1995).

ance links are costly, each bank individually would find it optimal to insure as little as possible. Because of the possibility of contagious effects, liquidity insurance depends on the participation of and coordination between all financial institutions in a system. Thus, the formation of private liquidity co-insurance contracts is conceptually close to coordination games played on graphs with local substitutes such as studied by Belhaj, Bramoullé and Deroian (2014); Bramoullé and Kranton (2007); Galeotti et al. (2010).

Lastly, our work relates to a tradition of network formation games as pioneered by works of Bala and Goyal (2000), Jackson and Wolinsky (1996), and Jackson and Watts (2002*b*,*a*). Jackson and Zenou (2014) provide a recent overview of this field of research.[3] While our models do not build directly on the work by Jackson, it is useful to briefly introduce the notion of pairwise stability as a criterion for the stability of a graph configuration (Jackson and Wolinsky, 1996). A graph g is said to be pairwise stable if

$$\begin{aligned} &\text{(i)} \quad \forall ij \in g, \quad Y_i(g,v) \geq Y_i(g-ij,v) \quad \text{and} \quad Y_j(g,v) \geq Y_j(g-ij,v) \\ &\text{(ii)} \quad \forall ij \notin g, \quad Y_i(g,v) < Y_i(g+ij,v) \quad \rightarrow \quad Y_j(g,v) > Y_j(g+ij,v), \end{aligned} \tag{1.1}$$

with ij denoting an edge between node i and j, v denoting the value created in the graph, Y_i and Y_j denoting the value allocation to node i and j respectively, and $g - ij$ and $g + ij$ denoting the graph that would be created by deleting edge ij or adding it respectively. The two conditions thus express that no pair of actors in the population would want to delete an existing link (i) or add a new link (ii). Jackson and Wolinsky further show that stable networks are not necessarily efficient and provide rules for which networks are efficient in terms of costs and benefits from

---

[3] For textbook overviews cf. Jackson (2008) or Goyal (2007).

links.[4] Other papers have extended this analysis to dynamic link formation when the process is unilateral (Bala and Goyal, 2000), when the link creation process is bilateral (Watts, 1999), to dynamic network evolution with stochastic perturbation, which aids to select among pairwise stable networks (Jackson and Watts, 2002*b*), and to network formation processes between players with heterogenous value and costs from forming links (Galeotti, Goyal and Kamphorst, 2006). It is to this tradition of studying strategic network formation games and the efficiency of the resulting network structures that our work relates.

1.2 Contributions to the literature

Our work mainly contributes to an understanding of the formation of interbank exposure networks. We contribute to this literature both with empirical findings and with theoretical results. The dynamic network formation model in Chapter 4 also contributes to the literature on coordination games on graphs. In the remainder of the section we highlight the results of each chapter and its contribution to the literature.

1.2.1 Empirical evidence for varying roles of interbank markets

The first chapter, *The Purpose of Interbank Markets*, is an empirical study of drivers of the German interbank market. The chapter begins by introducing the German banking sector with its three different bank types that make up universal banks in Germany: savings banks, cooperative banks, and private commercial banks. Due to the difference in governance structures of banks the German example allows us to develop testable hypotheses based on competing theories of interbank lending. The chapter tests these hypotheses using 43 quarters (2002-2012) of confidential data

---

[4] Jackson (2003) provides an early overview of the literature in the area of network formation, stability, and efficiency.

on the German banking sector and interbank market. We find that banks use the interbank market for liquidity co-insurance, which is consistent with the traditonal models of interbank lending.

The empirical results show a diversified picture in which the liquidity management function differs depending on the type of bank. Its importance is higher for regionally-focused credit cooperatives and savings banks than it is for private commercial banks. Moreover, we can identify a distinct effect for private banks. For private banks, increases in interbank liabilities are shown to correlate with a proxy for the bailout probability of banks. The chapter thus offers empirical support for an emerging literature on strategic behaviour in interbank markets and highlights the need to extend the traditional model. Lastly, it also introduces the Glasserman & Young indicator as a balance sheet-based proxy indicator for systemic importance.

1.2.2 Interbank lending without liquidity shocks

Motivated by the empirical findings the second chapter, *The Emergence of Interbank Exposures*, studies a model of optimal bank behaviour in which an alternative driver of financial co-exposures is considered. In order to complement the baseline model, which studies interbank lending as a mechanism of private liquidity co-insurance, we study a model in which liquidity co-insurance considerations are set aside. Instead, we assume that banks have access to profitable but risky investment opportunities and that an exogenous bailout probability exists.

We first introduce some stylised facts that document how different the structure of bank balance sheets are between different countries. In order to study bailout probabilities we introduce a flexible function that takes uncertainty of the regulator as well as an indicator for the systemic importance of banks as input variables.

Again, we use the Glasserman & Young indicator as a proxy for systemic importance. The function is flexible enough to model both smooth and step-sized functions, and parameters can be chosen so that the probability of bailout is either always zero, or liabilities are always guaranteed. The functional form has been chosen to facilitate empirical work estimating its parameters in different jurisdictions.

We show under fairly general conditions that even in the hypothetical absence of liquidity shocks, under some conditions the presence of some positive level of conditional liability guarantees can lead to interbank exposures as an equilibrium outcome. The results show that such an equilibrium is characterised by banks of different sizes and asymmetric bank behaviour. Some banks are active only as lenders with others investing in a productive technology while borrowing in the interbank market. It is interesting that starting from no heterogeneity at all, the simple presence of uncertain bailout probabilities leads, at a highly stylised level, to a banking equilibrium with banks of heterogenous sizes in which some small banks act as liquidity providers and large banks invest in profitable investment opportunities.

Finally, we derive an equilibrium interest rate which contains the parameters characterising the bailout probability. Thus, we can study the equilibrium interest rate as a function of both regulatory uncertainty and bank-specific factors.

1.2.3 Endogenous financial network formation with liquidity shocks and non-zero bailout probabilities

In the third chapter, *Coordination and Competition in the Formation of Financial Networks*, we take the empirical results and the model results from the previous chapter as a motivation to specify a model of financial network formation. We introduce a generalisation and extension of the seminal work of Allen and Gale (2000) that considers endogenous formation of bilateral liquidity co-insurance links between banks in a n-region economy. Contrary to the work of Allen and Gale we take the agency of banks into account and study profit-maximising banks that bargain with depositors and enter insurance contracts with each other. Both a static and a dynamic model of the endogenous formation of interbank liquidity co-insurance links are examined. In an extension of the model we further consider the role of non-zero bailout probabilities and how they affect the link formation of banks.

We introduce a novel way to study liquidity co-insurance that considers an iterative market clearing process and uncertain liability magnitudes. The approach is flexible and accounts for the fact that renegotiations of debt contracts occur frequently and exact exposures can be unknown due to complex co-exposures to assets combined with speedy price adjustments of such assets. Based on this mechanism we formalise a game of liquidity co-insurance and show that contrary to previous findings it is not possible for banks with limited information to insure optimally against liquidity shocks in best-shot games. However, in a dynamic formulation of the model with best-response dynamics and learning, socially optimal insurance is a stable state. At the same time the welfare-maximising level of insurance comes at the cost of higher fragility of the resulting financial network and at the cost of inequality.

Lastly, we study an extension to the dynamic model that introduces non-zero bailout probabilities. Due to the presence of bailout probabilities banks with higher systemic importance, modelled as a relatively higher number of insurance links, can demand a higher share of the profits in a fragile liquidity co-insurance market. We show that the presence of non-zero bailout probabilities leads to the constrained best welfare and induces a higher stability of the private provision of liquidity co-insurance. Moreover, the dynamic process leads to interbank networks that at a level of stylised facts are consistent with the structure of interbank exposure networks documented empirically.

Chapter 2

The Purpose of Interbank Markets

Models of interbank markets usually assume that banks use interbank lending to balance out temporal or regional liquidity shocks. Reciprocal interbank loans or deposits are considered to be liquidity co-insurance (Diamond and Dybvig, 1983; Bhattacharya and Gale, 1987; Castiglionesi and Wagner, 2013). This traditional view is complemented by models that consider additional incentives for banks to be active in the interbank market. The German banking sector contains different types of universal banks that differ in their governance structure. Besides private commercial banks, it contains savings banks and cooperative banks, which are comparable in their activities but the former is publicly owned while the latter is private. This structure offers a controlled setting in which the purpose of interbank markets can be studied. We use confidential data from the Deutsche Bundesbank to examine those theories empirically. While the data supports the theory of liquidity co-insurance, especially for regionally-focused savings banks and credit cooperatives, further incentives play a role for private banks. In order to identify potential strategic behaviour, we examine whether changes in interbank liabilities affect the bailout probability of banks. In the absence of extensive evidence on what determines bank bailouts, the study uses a proxy for the bailout probability, which is a balance sheet-based indicator for the systemic importance of banks derived from work of Glasserman and Young (2015). We find that increasing interbank liabilities correlate with increases in this indicator for the bailout probability. This finding suggests that theories of interbank lending, while not replacing liquidity co-insurance as an assumption, need to consider strategic behaviour as additional drivers of the interbank market.

It is not only since the 2007-2009 financial turmoil that interbank exposures have been studied with increased interest. While interbank lending can provide banks with liquidity at times of need and allows them to employ excess funds profitably, it also generates a form of systemic risk in the banking system. When one institution cannot fulfil its obligation to its creditors, the creditors themselves may experience financial distress. Rochet and Tirole (1996) argue for the possibility of contagious failures in the context of showing how interbank deposits can prevent bank defaults. Allen and Gale (2000) famously describe this phenomenon of financial contagion and have motivated a large literature on the link between systemic risk and structural features of the financial system. This extant field of literature has developed from the work of Eisenberg and Noe (2001). It spans theoretical work (Gai and Kapadia, 2010; Gai, Haldane and Kapadia, 2011; Haldane and May, 2011) as well as empirical analyses of systemic risk of financial systems (Angelini, Nobili and Picillo, 2011; Boss et al., 2004; Cont, Moussa and Santos, 2013; Craig and von Peter, 2014; Degryse and Nguyen, 2007; Iyer and Peydro, 2011; Mistrulli, 2011; Upper and Worms, 2004).[5] Increasing interbank exposures have been identified as one of the major drivers of the

---

[5] Ladley (2013) provides a concise overview of some of the main works, also cf. Bartram, Brown and Hund (2007).

financial crisis of 2007-2009 (Brunnermeier, 2009). However, despite the significance of interbank liability exposures for systemic risk in financial markets, few explanations or systematic descriptions of the strategic behaviour driving these exposures exist (cf. Eisert and Eufinger, 2013 for an exception).

How to manage systemic risk in the light of increased co-exposures and higher interconnectedness of banks is a question of importance to both economists and policy makers. This chapter aims to contribute to identifying the factors that influence interbank exposures. Before presenting the results of a hypothesis test examining the implications of competing theories of interbank lending, we describe the German interbank market and present an identification strategy to isolate drivers of interbank market activities. To motivate the hypotheses, we present both the traditional view of interbank lending as well as complementary theories. Some models such as the one proposed in Chapter 3 ignore idiosyncratic liquidity shocks as a reason for interbank lending and show that an interbank market can emerge if interbank exposures affect bailout probabilities of banks. The ensuing hypothesis test uses constructs derived from the balance sheet data of German banks and some aggregated exposure information.

The chapter proceeds as follows. We first review relevant academic work that touches on drivers of the interbank market and on literature pertinent to strategic behaviour of banks in interbank markets. We then provide an overview of the structure of the German interbank market and the German financial sector as a whole in order to motivate the identification strategy. In a section on methodology, we present the main variables and the hypothesis test before discussing regression results. A similar regression analysis, testing the liquidity hypothesis and further hypotheses on the determinants of interbank markets, has been carried out in a Bundesbank-SAFE research project 'Interbank Intermediation' (Bluhm, Georg and Krahnen, 2016). Lastly, we discuss the implications of my findings both for theoretical work as well as for policy makers.

2.1 Competing theories of interbank exposures

Much of the literature on the behaviour of banks in interbank markets assumes that banks operate in the market in order to satisfy liquidity needs. This assumption is rarely questioned and often not even made explicit.

In order to study the purpose of interbank markets it is necessary to understand the mechanisms and drivers that lead to its existence. To date no conclusive examination of these incentives exists. However, a large literature has studied the consequences of interbank connections for the financial system, or how the complexity of interbank markets and the interconnectedness of banks create systemic risk. It is beyond the scope of this chapter to review that literature extensively. Some references to the main works are important to motivate this study though. Gai and Kapadia (2010) examine how different interbank network structures affect the potential threat of contagious defaults. Gai, Haldane and Kapadia (2011), Haldane and May (2011), and Battiston et al. (2012*b*), amongst many others, further this line of thinking by introducing the effect of complex network structures and studying the risks inherent to varying degrees and types of connectedness. Other more recent work in this area includes Cabrales, Gottardi and Vega-Redondo (2014), Elliott, Golub and Jackson (2014), Ladley (2013), and Upper (2011). Acemoglu, Ozdaglar and Tahbaz-Salehi (2015), Battiston et al. (2012*a*), and Glasserman and Young (2015) study how and whether the actual structure of networks affects the risk of contagion. Most of the works in these areas assume the structure of interbank networks as being determined ex-ante. They differ in their results on the effect of the structure of interbank networks on default propagation. Some authors argue that the underlying structure can be found to significantly affect the robustness of financial networks, while others argue that, regardless of the underlying structure, the magnitude of a shock determines whether contagious defaults will occur. Some works that consider emergent interbank networks are discussed in the next subsection. Even when interbank loans are studied as the outcome of some endogenous process, it is usually done under the assumption that banks face liquidity shocks and co-insure each others against uncertain future liquidity needs.

Some models have studied other incentives for entering interbank exposures. They are discussed together with the model in Chapter 3 in order to motivate the hypothesis that interbank markets serve as a mechanism to manage the bailout probability of a bank (either through the private sector or a government) in the case of financial distress.

2.1.1 Liquidity needs hypothesis

Banks act as financial intermediaries who issue long-term loans using short-term fluctuating demand deposits transforming illiquid assets into liquid liabilities. In this context interbank lending is modelled as a deterministic process based on probabilistic fund allocation. In their canonical work in this area, Diamond and Dybvig (1983) argue that given deposit insurance, banks improve welfare by balancing regionally and temporally dispersed liquidity needs. This is a functional view of banking rather than a theory of bank behaviour. In their three-period model ($T = 0, 1, 2$) Diamond and Dybvig assume that banks are mutually owned and resolved in the last time period. Assuming that liquidity needs are randomly distributed and liquidity shocks independent, large enough banks would be able to balance out fluctuations in liquidity demand. If a bank cannot fulfil its obligations to depositors, a lender of last resort can provide needed short-term liquidity in order to prevent bank runs (Bhattacharya and Gale, 1987). How a lender of last resort should operate is of great theoretical importance as well as practical relevance, but is not the focus of this chapter. Freixas, Martin and Skeie (2011, 2658) provide a concise summary of this theory: "[the] main purpose of [the interbank market] is to redistribute the fixed amount of reserves that is held within the banking system".[6]

Models in the tradition of Diamond and Dybvig (1983) consider banks to invest aggregate deposits in order to generate a return that is then shared among depositors. In the original three-period model, banks can choose to allocate funds to short-term and long-term investment technologies at $T = 1$, when they learn the distribution of types in the population of agents.[7] Bhattacharya and Gale (1987) and Bhattacharya and Fulghieri (1994) present a model in which banks need to commit to their investment in long-term and short-term technologies before they learn the types of their depositors. Thus, in their model banks face liquidity shocks at $T = 1$ because they either invested too much in the short-term technology (which leaves an individual bank with excess liquidity) or too little (which would leave some depositors empty-handed). Bearing in mind the assumption of a countably infinite number of banks and a publicly known distribution of patient and impatient depositors, banks can improve their utility by lending and borrowing from and to each other. Rather than default on depositors in the case of a liquidity shortfall, banks can draw on interbank deposits at $T = 1$ to satisfy liquidity needs. This insurance assumes of course that

---

[6] Also cf. Ladley (2013). In their model bilateral interest rates determine the lending and borrowing appetite of banks, who can only be either borrower or lender.

[7] It is assumed that there are two types of agents in the population. Patient agents, who only value consumption at $T = 2$ and impatient agents, who only value consumption at $T = 1$.

most banks hold deposits with each other, so that a bank with a shortfall has access to a bank with excess liquidity.

It is this view of shared interbank deposits or lending that became the dominant theory of interbank markets. Freixas and Holthausen (2005) extend this model to cross-country lending and in that context consider asymmetric information between countries. Freixas and Rochet (2008) provide a textbook overview of the liquidity provision role of the interbank market. Some models study the formation of lending or deposit contracts and thus the formation of interbank markets. These works largely follow the tradition of banks interacting to balance liquidity shocks such as in Castiglionesi and Navarro (2011) or Acemoglu, Ozdaglar and Tahbaz-Salehi (2015).

Taken together, these works explain the function of the interbank market by its ability to resolve liquidity shocks and to provide liquidity co-insurance to banks. This type of liquidity co-insurance has been studied extensively, also with regards to a tradeoff between the access to liquidity and exposure to contagious shocks (cf. Brusco and Castiglionesi, 2007; Castiglionesi and Wagner, 2013 or Ladley (2013) amongst others).[8] The following hypothesis summarises the traditional view of interbank markets and allows one to test it empirically:

H1 Banks manage liquidity needs through the interbank market: an increase in liabilities to other banks is positively and strongly correlated with an increase in liquidity needs of a bank.

---

[8] Banks engage in interbank lending to deal with liquidity shocks, but (leveraged) banks hoard liquidity when they face a potential future demand for liquidity (precautionary demand motive; Acharya and Skeie, 2011; Ashcraft, McAndrews and Skeie, 2011; Diamond and Rajan, 2011; Gai and Kapadia, 2010; Gale and Yorulmazer, 2013). Liquidity hoarding can also be motivated by avoiding predatory trading (Brunnermeier and Pedersen, 2005), which is selling illiquid assets on spot market at a discount, and speculative motives (arbitrage through taking advantage of fire sales; Gale and Yorulmazer, 2013).

2.1.2 Strategic positioning hypothesis

Some models have been proposed that consider strategic behaviour in the interbank market, either complementing liquidity co-insurance or replacing it. Babus (2014) offers a model in which banks engage in interbank lending in order to minimise the risk of contagion in the case of defaults. While banks form links in order to insure themselves against liquidity shocks, they aim to maximise their degree (number of counter parties) and minimise individual exposure. The Babus model in particular raises the question of why banks should act in a manner that optimises global features of the market. As Farhi and Tirole (2012) show, increasing the riskiness of balance sheets (and thus the risk of contagion) can be beneficial in the light of government intervention. In their discussion of the formation of bubbles, Brunnermeier and Oehmke (2013) argue that bubbles arise because traders do not act in the interest of a functioning market, but maximise expected profit based on their own information and payoff structure. For instance, a trader selling under pressure takes into account her losses, but not those that accrue to the overall system by depressed prices as a consequence of her actions. While the Babus model offers a benchmark for minimising exposure risk, its underlying assumptions are somewhat incomplete.

Farhi and Tirole (2012) show how government intervention in the form of bailouts can distort the interbank market. They show that when governments cannot tailor their policies sufficiently, it is optimal for banks to take on extra leverage as long as they do so in a coordinated fashion, because increasing the riskiness of balance sheets of individual banks is a strategic substitute in the presence of government intervention. Others have argued that banks coordinate their behaviour in making investment decisions in order to fail together and benefit from ensuing government support (Acharya and Yorulmazer, 2007; Eisert and Eufinger, 2013) and that banks can shift systemic risk to the government by such coordinated behaviour (Acharya, 2009). Eisert and Eufinger's (2013) model is one example in which banks enter circular lending relationships across national borders. If there is a fixed bailout probability in case of a bank's default in each country, entering lending relationships that involve more countries minimises the risk of an uninsured creditor. Farhi and Tirole and Acharya and Yorulmazer argue for a collision between banks in order to take advantage of a government subsidy. In contrast, in the model of Eisert and Eufinger it is optimal for a bank to enter interbank lending relationships (cross-border) regardless of the action of other banks. Similarly, Leitner (2005) argues that banks have a private incentive to enter potentially risky interbank lending relationships, because it increases the likelihood of a private sector bailout. In his model agents face a tradeoff between exposing themselves to a higher contagion risk, while at the same time insuring themselves. The historical rescue of Long Term Capital Management (LTCM) has shown that private consortia can rescue financial institutions.

As argued above most existing models assume that interbank lending exists as a consequence of liquidity shocks. Chapter 3 develops a model showing that even in the absence of idiosyncratic liquidity shocks interbank markets can emerge if interbank exposures affect the perceived probability of a bank to be bailed out in the case of default. The work adds to complementary theories of the interbank market and offers an additional explanation for why interbank exposures can emerge. Whether a bailout would be private or government driven is inconsequential to the model. For interbank markets to emerge uncertainty regarding bailouts needs to exist. The extent and nature of this uncertainty depends on the market environment and jurisdiction in which banks are based. The 2007-2009 financial crisis provided a range of examples, where bank bailouts have been decided on a case-by-case basis. The model therefore uses a cumulative probability function that provides an estimate of the likelihood of bank liabilities being guaranteed. The function contains two parameters, a bailout threshold and an uncertainty parameter, which can be estimated for different temporal and regional conditions to reflect political realities. As this study is confined to just one jurisdiction, it unfortunately cannot address differences between jurisdictions.

Interbank borrowing is rational for banks if there exists uncertainty regarding a bailout. However, it is never optimal for all banks in a system to engage symmetrically in interbank lending and never optimal if no uncertainty regarding bailouts exist. The model in Chapter 3 shows that if a positive bailout probability exists and it is uncertain, some banks will lend heavily to others, who invest in a risky technology. They employ a representation of a bailout probability that links the balance sheet composition of a bank to the likelihood of it being bailed out in the case of insolvency using the work by Glasserman and Young (2015) to describe the systemic importance of a bank.

This overview of the emergent literature on alternative drivers of the interbank market allows one to formulate a testable hypothesis. In addition to satisfying liquidity needs, private banks may rely on the interbank market in order to manage their probability of being bailed out when distressed. As Eisert and Eufinger (2013) argue, for instance, the motivation to engage in circular lending relationships stems from protecting uninsured depositors. A higher likelihood of bailout reduces the default risk of loans for creditors, which implies lower borrowing costs for such banks. Thus, if otherwise comparable banks of which some are publicly owned or their liabilities guaranteed, one ought to expect those without guarantees to use the interbank market strategically to improve their bailout probability. The following hypothesis summarises this expectation:

H2 For private banks, an increase in liabilities to other banks is positively correlated with an increase of the bailout probability of a bank.

2.2 The banking sector and interbank market in Germany

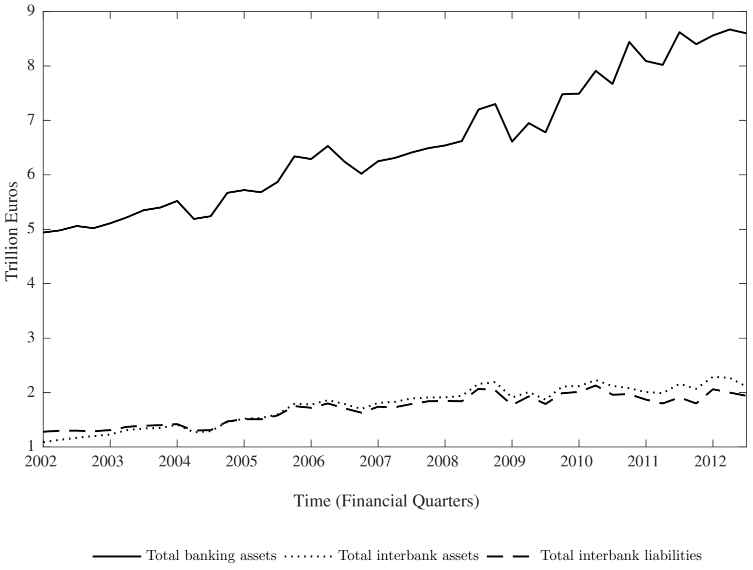


Figure 2.1: Total banking assets and interbank lending in Germany

The graph shows total assets of banks, i.e. the size of the banking sector in Germany, and compares them to total interbank loans and advances (interbank assets), as well as interbank liabilities. Source: Created by author, based on Monatliche Bilanzstatistik, Deutsche Bundesbank, November 2013.

The structure of the German banking sector can be used to identify various drivers of banks to be active in the interbank market by comparing changes in interbank liabilities of different bank types. Before outlining the method of identifying such drivers, we provide a brief overview of the German interbank market. The sum total of bank assets grew from 6.3 trillion Euros in 2002 to 8.7 trillion Euros in 2012 (non-inflation-adjusted), with total interbank liabilities growing from 1.8 trillion Euros to 2.3 trillion in the third Quarter of 2008 and dropping to 2 trillion in 2012 (cf. Figure

2.1). This compares to a GDP of 3.5 trillion USD in 2012.[9] This simple comparison illustrates the importance of the interbank market in Germany. On-balance-sheet interbank liabilities are equivalent in size to two thirds of GDP.

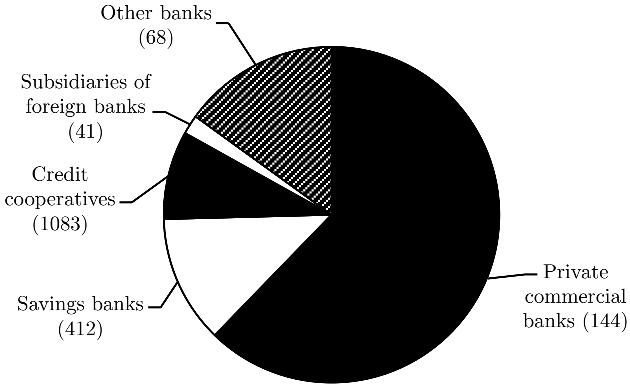


Figure 2.2: The German banking sector in 2012

The figure shows the composition of the German banking sector by asset size and states the number of banks for each type. The graph is for the third quarter of 2012, when the size of the banking sector was 8.6 trillion Euro. Source: Created by author, based on Monatliche Bilanzstatistik, Deutsche Bundesbank, April 2014.

The German interbank market can also be studied from a structural perspective using measures from network theory, where liability exposures constitute links between banks. While not the focus of the chapter, it is important to note that the structure of the interbank market is stable. Interbank exposures are part of on-balance-sheet interbank lending and borrowing, which form part of variables used in this study. The regressions control for structural factors to ensure that they do not drive results. Domestic bilateral exposures are reported to the central bank in quarterly intervals if they are larger than 1.5m EUR.[10] Roukny, Georg and Battiston (2014) provide a detailed network-based description of the German OTC market for credit exposures as well as derivative exposures. They find that the structure of the

---

[9] Cf. http://data.worldbank.org/indicator/NY.GDP.MKTP.CD [Accessed 11 January 2015].

[10] It is important to note that reported exposures includes all liabilities, including off-balance-sheet exposures and exposures from derivatives not necessarily shown on the balance-sheet. At the same time, on-balance-sheet liabilities will also include liabilities smaller than EUR 1.5m. So, while both measures are informative in conjunction, they cannot be compared directly.

interbank network is mostly stable, also throughout and after the 2007-2009 financial crisis. However, they identify a spike in derivative exposures in its run-up. Both for credit exposures and derivative exposures it is shown that few important players exist in the market, which concentrate exposures. Table 2.7 shows some further network measures. In 2012, 1681 banks had 21741 bilateral liability exposure relationships between them. One can see from some simple network measures that the interbank exposure network in Germany exhibits a small diameter (4 or 5), which means that all banks are separated by liability exposures through at most 4 other banks.[11] It shows that contagious shocks can reach most banks quickly. At the same time one sees high clustering (larger than 0.8) and a low density (smaller than 0.01), which shows that while banks tend to interact with similar counter parties when they lend to or borrow from each other, most banks do not share bilateral exposures.[12]

However, it would be misleading to regard the German banking sector as a collective of comparable entities. It comprises private commercial banks, both domestic banks and subsidiaries of non-German banks, state-owned banks, savings banks, credit cooperatives, and other banks or bank-like institutions. For instance, a financial services arm of a consumer company, such as a car manufacturer that offers financing solutions to its customers, holds a banking license. Volkswagen Bank GmbH or Mercedes-Benz Bank AG are examples of such entities. This analysis focuses on universal banks, also frequently referred to as credit banks, which take deposits, or otherwise raise capital, in order to lend to consumers and businesses. These bank types perform the characteristic maturity transformation function described by Di-

---

[11] The diameter of a network is the longest shortest path between any two nodes of a network, cf. Jackson (2008) or Appendix A.

[12] We use transitivity as a measure of clustering. It is the extent to which so-called transitive triplets are present in the network. Density is the existing number of links in a network divided by the possible number of links in a network. Appendix A contains precise definitions of these measures. Also cf. Jackson (2008) or Newman (2010) for details.

amond and Dybvig (1983) in that they transform illiquid assets (such as loans) and liquid liabilities (such as deposits). Furthermore, focusing on these banking groups avoids distortions to the analysis that could arise from including special-purpose banks such as state-owned banks (Landesbanken) or development banks, both of which have very specific objectives that are not necessarily related to maturity transformation.

Credit banks comprise domestic private commercial banks, subsidiaries of foreign commercial banks, credit cooperatives, and savings banks. These banks pursue similar business models even though they differ greatly in their governance structure. As the ultimate ownership and control of foreign private commercial banks rests in non-German institutions, those banks are excluded from the analysis because no information on the parent entities is available in the data. It is apparent from the composition of the balance sheets of these banks (cf. Table 2.1) that the main source of funding is derived from foreign bank liabilities, presumably held against the parent bank. The majority of interbank liabilities (and often of all liabilities, cf. Table 2.2) are long-term and with foreign banks.[13] We thus distinguish the four types of credit banks in this section and subsume all remaining banks under the label 'other banks'. In the ensuing description we describe all entities with a banking license in Germany as part of set B, (domestic) private commercial banks members of set $U \subset B$, credit cooperatives members of set $C \subset B$, and savings banks members of set $S \subset B$, where U, C, and S do not overlap. Figure 2.2 shows that, whilst in terms of quantity the majority of banks are not private commercial banks but savings banks and credit cooperatives, private commercial banks make up for more than half of assets in the German banking sector.

---

[13] This observation supports limitations of Minoiu and Reyes's (2013) study in the sense that widespread claims of an increasing connectedness of the financial system may just reflect an increase in the globalisation of the financial industry.

	Private commercial banks	Savings banks	Credit cooperatives	Foreign commercial banks	Other	Total
Short-term	560	42	33	15	407	1057
Long-term	835	45	34	81	61	1055
Total	1395	87	67	96	467	
Domestic	684	83	65	46	404	1282
Foreign	711	4	2	50	63	829
Total	1395	87	67	96	467	

a) Interbank assets in billion Euros

	Private commercial banks	Savings banks	Credit cooperatives	Foreign commercial banks	Other	Total
Short-term	566	141	89	21	140	956
Long-term	778	26	16	91	70	981
Total	1344	167	105	111	210	
Domestic	693	166	103	12	163	1137
Foreign	651	1	2	99	47	801
Total	1344	167	105	112	210	

a) Interbank liabilities in billion Euros

Table 2.1: Composition of German interbank assets and liabilities in 2012

The table shows aggregate interbank assets and liabilities for four banking groups in Germany. Private commercial banks excludes foreign commercial banks. It categorises interbank lending and borrowing according to location of counter party (domestic and foreign) and maturity of contract (short-term and long-term). Short-term is defined as maturities of less than one month. Differences in sums are due to the effects of rounding.

Private commercial banks comprise large publicly-traded banks such as Deutsche Bank AG, Commerzbank AG, or Deutsche Postbank AG as well as smaller private banks that may have a regional or industry focus. Bankhaus Sal. Oppenheim[14], HSBC Trinkaus & Burkhardt AG, and HSH Nordbank AG are examples of such smaller banks. Private commercial banks are predominantly structured as profit-oriented companies and do not enjoy federal or municipal government guarantees for their liabilities. Their interbank lending activities (cf. Table 2.1 panel a) and borrowing activities (cf. Table 2.1 panel b) are split approximately evenly between domestic and non-German counter parties, with a tendency to longer-term contracts. Moreover, private commercial banks in aggregate have approximately as many interbank assets as interbank liabilities. This intra-bank-type balance of lending and borrowing is consistent with the intermediation function of the interbank market which relies on interbank liabilities to channel excess funds to profitable investment opportunities.[15] Given the regional focus of credit cooperatives and savings banks one would expect less such channeling of funds towards investment opportunities (interbank assets) by these bank types, which is indeed consistent with the data. Commercial bank deposits are insured up to 100,000 Euro by federal law and, in addition, private banks operate a mutual trust fund through which they self-insure deposits beyond that level (Bankenverband, 2015).

Savings banks constitute a central part of the German banking system. While in terms of their services and activities comparable to private commercial banks, savings banks are publicly owned and structured accordingly (Schlierbach and Püttner, 2003). Savings banks have special relationships to their respective state banks (‘Lan-

---

[14] Sal. Oppenheim jr. & Cie. AG & Co. KGaA

[15] Cf. Farboodi (2014) for a recent contribution to this literature and an overview of important works.

desbanken'), which provide a source of refinancing and are predominantly owned by local or municipal government, which can be one city or a union of several cities. This control structure implies that liabilities are ultimately publicly guaranteed by the financial prowess of the city or collective of cities backing a savings bank. Moreover, in addition to the deposit insurance provided by the federal government, savings banks as a collective operate an additional deposit insurance fund.

Credit cooperatives are mutually owned by depositors and are private banks. These institutions are similar to savings banks in their regional focus, but are not controlled or owned by local government. The extent of interbank market activities of credit cooperatives is comparable with that of savings banks (cf. Table 2.1), especially when comparing them in percentage terms (cf. Figure 2.3). Moreover, both bank types almost exclusively transact with domestic counter parties and have higher interbank liabilities than assets. While interbank assets tend to be both long-term and short-term, liabilities are predominantly short-term, which is consistent with the hypothesis that banks use the interbank market to satisfy liquidity needs.

In summary, the German banking sector consists of a range of bank types of which domestic universal banks make up approximately 80% of total assets and more than 90% of banks.[16] These universal banks comprise three types differing markedly in their governance structure: private commercial banks, publicly-owned savings banks, and mutually-owned but private credit cooperatives.

---

[16] Domestic universal banks is equivalent to credit banks 'Kreditbanken' in standard Bundesbank classification, but excluding subsidiaries of international banks.

2.3 Identifying drivers of interbank markets

In order to conclusively investigate whether incentives other than liquidity management are driving interbank markets, the German banking sector, in which universal banks with similar business models but different governance structures operate, offers a suitable setting. While one would expect differences in interbank lending behaviour between private commercial banks and the more regionally oriented credit cooperatives and savings banks, the latter two are comparable with one being publicly owned and the other one privately owned. We thus use a difference-in-difference (diff-in-diff) model to examine whether increases in bailout probabilities correlate positively with increases in interbank borrowing for credit cooperatives in excess of what would be expected based on savings banks interbank market behaviour. No direct measure of bailout probabilities exist of course. The analysis therefore relies on a proxy indicator, which we present in this section. The data used in this analysis combines two confidential data sets available at the Deutsche Bundesbank. We first describe the data before presenting the identification strategy used to test the competing hypotheses. Lastly, we comment on the variables and analysis.

2.3.1 Data

According to section 7 of the German Banking Act (KWG) of 1998 the supervision of banks rests with the Deutsche Bundesbank. Basis for the analysis are two self-reported datasets collected by the Deutsche Bundesbank. The first exists due to directive 2006/48/EC. According to this European Commission directive banks are required to report balance sheet information on a monthly basis in the 'Monatliche Bilanzstatistik' (BISTA). The second is based on sections 13 and 14 of the German Banking Act, which require banks to provide quarterly reports of bilateral liability exposures in which they act as creditors for all credit exposures larger than EUR 1.5m (collected by the Millionenkreditevidenzzentrale or credit register). Banks report exposures at the end of the quarter if at any point during the quarter this threshold has been exceeded. The exposure data contains all on and off balance sheet exposures between institutions in Germany. Thus, only for domestic banks bilateral exposures are known. The balance sheet information contains both domestic as well as international loans and advances to banks, as well as domestic and international bank liabilities.

For a satisfactory analysis of the role of interbank markets both sets of information are combined into one dataset. The dataset brings together balance sheet information as well as bilateral liability exposures on a quarterly basis for 43 periods from 2002 Q1 until 2012 Q3. In the time period between 2002 and 2012 one sees between 1741 (2003Q1) and 1762 (2009Q2) active banks in the interbank market that between them have over 20000 bilateral exposure relationships in each period. Due to reporting requirements, only exposures greater than EUR 1.5m (at some point of the reporting window) are included in the data. Table 2.7 offers some descriptive statistics of the total exposure network in each time period that include some network measures.

In order to work with the data, an extensive cleaning process as outlined below was necessary. It has been formalised in a software, which is now available as open source code.[17] Banks report liability exposures to firms as well as to other banks at a level of legal entity. Banks often encompass a number of legal entities. The data cleaning started with deleting all bank-firm liability exposures. Left just with bank-bank liability exposures at a legal entity level, exposures are aggregated to the level of bank holding companies. In the process, idiosyncrasies in the data (such as

---

[17] Available at: http://www.netgen-toolbox.org. Main software engineer is Tarik Roukny, Jens Krause is a co-developer.

double counting of exposures for specific legal forms of banks, different identifiers for creditors and debtors, as well as mergers and acquisitions) are resolved. The process is applied both to the balance sheet information as well as the bilateral exposure information, so that the resulting banks are fully consistent across datasets. The final dataset contains full information over a ten-year period of the bilateral liability exposures of banks, paired with all relevant balance sheet information on a quarterly basis.

2.3.2 Glasserman & Young indicator

To proxy the bailout probability of a bank we use a balance-sheet-based indicator for the systemic importance of a bank. We rely on work of Glasserman and Young (2015) who develop a measure for a threshold at which the failure of a bank would have contagious consequences. Given the small number of bank bailouts globally and the fact that they usually occur during crises rather then 'normal' times, it is difficult to measure accurately what influences the perceived or real probability of a bank to be bailed out. Anecdotally, banks most likely to cause contagious defaults in the case of their own default, thus posing a threat to the stability of the financial system as a whole, are more likely to be bailed out. We thus assume that the more likely contagious consequences, the more likely a bank would get bailed out.

We use A_i to denote the total assets of a bank i, which is sometimes just referred to as bank size, A_i^{IB} and L_i^{IB} to denote interbank assets and interbank liabilities respectively, as well as w_i to denote equity. In order to assess the importance of different banks, let $\beta_i \in [0,1]$ be as in Glasserman and Young (2015):[18]

$$\beta_i = \frac{L_i^{IB}}{L_i^{IB} + L_i^{O}}, \tag{2.1}$$

where L_i^O are liabilities to outside of the financial sector such as deposits. β is a measure of relative exposure of the banking sector to an institution compared to the exposure of non-banking actors. Glasserman and Young show that the likelihood of contagion in financial systems from shocks to individual entities depends on the β_is of those entities. Their theorem 1 states that contagion from one institution to a set of banks D excluding i is impossible if the following condition holds true:

$$\sum_{j \in D, j \neq i} w_j / w_i > \beta_i(\lambda_i - 1), \tag{2.2}$$

where w_i is the equity (or net worth) of a bank and

$$\lambda_i = (L_i^O / w_i), \tag{2.3}$$

constitutes the leverage of non-banking liabilities. Simplifying slightly, the higher an entity's β_i, the higher the likelihood that adverse shocks to this entity will spill over to other entities in the system.

We use the RHS of Eq. 2.2 as a proxy for bailout probability and define ψ_i as the G&Y indicator for a bank:

$$\psi_i = \beta_i(\lambda_i - 1). \tag{2.4}$$

The higher the indicator, the higher the bailout probability. The larger the liabilities

---

[18] The Glasserman and Young β_i is not to be confused with that of the CAPM model, to which it is unrelated.

to other banks relative to total liabilities, the higher the indicator. The larger the ratio of non-financial assets to equity, the larger the indicator. For the sake of the present analysis we thus assume that those banks most exposed to the real economy (leverage ratio excluding banks, λ_i) and to whom the banking sector is disproportionally exposed (higher β_i) are more likely to be bailed out. Of course the absolute size (A_i) of an institution is relevant here, which is why all regressions include size as a control.

2.3.3 Main variables and hypothesis test

In order to test the hypotheses developed above one needs to overcome two challenges. The first is identifying the variables described in the hypotheses, including interbank borrowing and an indicator for the probability of being bailed out. We refine the developed hypotheses to make them testable given the available data. Second, one needs to account for the fact that bilateral lending and borrowing decisions are influenced by an array of factors such as the position of a bank in the interbank market, leverage, and other bank-specific factors that are not relevant for the analysis.

It is impossible to determine the precise amount of interbank borrowing from balance sheet or exposure information. This would require one to know exact maturities of interbank loans and interbank credits of individual institutions. Assuming that at an aggregate level maturities of new loans or credits are similarly distributed as those of existing ones, which again seems to be a conservative assumption under stable macroeconomic conditions, we approximate interbank borrowing of a bank with the change in net liabilities to other banks ϕ_i:

$$\phi_i = \log\left(\frac{L^{IB}_{i,t}}{A^{IB}_{i,t}}\frac{A^{IB}_{i,t-1}}{L^{IB}_{i,t-1}}\right). \tag{2.5}$$

Variations of the analysis that are run as controls use net interbank borrowing at different maturities. Short-term interbank borrowing are all loans with a maturity of less than one month, denoted by ϕ_{ST}. Long-term interbank borrowing is denoted by ϕ_{LT} and summarises all loans with longer than a one-month maturity. In addition to net interbank borrowing, alternative specifications of the model are studied using gross interbank borrowing, which is simply

$$\phi_i' = \log\left(L_{it}^{IB}/L_{it-1}^{IB}\right). \tag{2.6}$$

A liquidity need can arise because banks redistribute liquidity in an economy or because of regional or temporal liquidity shocks. However, neither the daily liquidity need of banks, nor their precise day-to-day interaction on the interbank market are readily available. In this work we therefore ignore bilateral interactions. We consider two sources of liquidity needs: loans and deposits. As one cannot observe maturities of loans, we assume that in each period new loans on average have the same maturity as old loans, so that approximately the same amount of loans expire as are granted. This assumption seems valid in most periods as long as macroeconomic conditions are stable. The regressions include time fixed effects to account for changes in these conditions. So, the difference in loans to households and firms (identified simply as loans in the following) between two periods is approximately the net lending to households and firms. Similarly for deposits. The difference in deposits between two periods is approximately the inflow or outflow of liquidity. We therefore define liquidity need of a bank θ_i:

$$\theta_i = \log\left(\frac{H_{i,t}}{D_{i,t}}\frac{D_{i,t-1}}{H_{i,t-1}}\right), \tag{2.7}$$

where $H_{i,t}$ and $H_{i,t-1}$ are bank i's loans to households and firms in period t and $t-1$ respectively, and similarly for $D_{i,t}$ and deposits.

With these definitions, hypothesis H1 becomes testable. We may formulate a general expectation for all banks and, given the access to alternative means of funding such as bond markets of private commercial banks, a separate one for commercial banks.

H1a An increase in ϕ_i is positively and strongly correlated with an increase θ_i.

H1b The correlation between an increase in ϕ_i and an increase in θ_i, while positive, is smaller for private commercial banks than it is for savings banks and credit cooperatives.

In order to test whether private banks manage their liabilities to other banks strategically as argued in Chapter 3 and outlined in the section above, we use the interperiod difference of the G&Y indicator $\Delta\psi_i$ as an explanatory variable:

$$\Delta\psi_i = \log\left(\frac{\psi_{i,t}}{\psi_{i,t-1}}\right). \tag{2.8}$$

To test whether this indicator is the best proxy for strategic behaviour in the interbank market is beyond the scope of this study, but the findings are in line with theoretical arguments motivating the hypotheses tested. In order to determine whether interbank market activities of private banks are at least partially motivated by influencing their bailout probability it is necessary to isolate what relationship between interbank borrowing and the change in the G&Y indicator would be expected purely due to their business model and the balance sheet identity. Fortunately, savings banks and credit cooperatives are comparable in their business model so that savings banks provide a baseline for comparison as a public bank with guaranteed liabilities. Controlling for bank and time fixed effects, estimating a diff-in-diff model for those two bank types allows one to estimate the desired effect. One can thus test H2 as follows:

H2 For credit cooperatives there is a significant positive correlation between ϕ_i and ψ_i above the benchmark established by savings banks.

2.3.4 Control variables

The interbank market is ultimately determined by bilateral interbank lending and interbank borrowing decisions that are influenced by a multitude of bank-specific variables and macroeconomic factors. In order to account for these factors, we use a fixed effects model to account for bank-specific factors and include time period dummy variables. It has also been documented that the German interbank market is tiered and that characteristics such as bank size determine which bank is a central actor in the market (Craig and von Peter, 2014). In addition to controlling for size, it is therefore necessary to also control for the position of a bank in the interbank market.

Before discussing control variables, some notation is necessary. A liability exposure between bank i and bank j is identified as l_{ij}. In this relationship l_{ij} represents the total liability exposure of i to j. For instance, if the exposure consists of an interbank loan, i is the creditor and j the debtor. We use bilateral exposures to derive some network measures used in addition to balance sheet items. The interbank network can be represented by the adjacency matrix $\mathbf{L} = [l_{ij}]_{i=1,j=1}^{n,n}$, which records all bilateral liability exposures between n banks. Let Ω_i^{out} (Ω_i^{in}) define the set of banks that are debtors (creditors) to i. $d_i^{out} = |\Omega_i^{out}|$ ($d_i^{in} = |\Omega_i^{in}|$) denotes the number of debtors (creditors) of a bank.

The most important control variable is bank size. Size is measured simply as total assets A_i. All changes in the overall balance sheet that are not part of the explanatory variables or the dependent variable are controlled for in addition to other structural factors likely to influence interbank activities. These controls include other assets (ΔA_o), changes in other liabilities (ΔL_o), and changes in equity (Δw). Leverage is defined as the size of the balance sheet divided by equity or A_i/w_i. The level of intragroup lending, denoted by G_i, is derived from bilateral exposure information and is the sum of exposures between subsidiaries of the same bank. The creditor-to-debtor ratio, denoted by R_i, is $\frac{\Omega_i^{in}}{\Omega_i^{out}}$ and controls for changes in the composition of lending counter parties of a bank. The centrality of a bank, denoted by C_i^e in the interbank market is measured by eigenvector centrality as defined in Jackson (2008), because it is sensitive to importance of the neighbours as well as to the number of counter parties of a bank.[19] Eigenvector centrality of bank i is the i-th entry of the eigenvector of $\mathbf{L}$ associated with the largest eigenvalue of the adjacency matrix.[20]

2.3.5 Diff-in-diff model and analysis

The analysis relies on the G&Y indicator as the main explanatory variable, which is a factor rather than a monetary difference in balance sheet items. It is thus necessary to treat all changes in balance sheet items as percentage changes rather than absolute changes. In order to estimate the model with OLS, logarithmic transformations are applied to the variables as appropriate. Given balance sheet items cannot be zero or negative, a simple logarithmic transformation of the form $\log(v)$ is used on the original variables v. In the case of first differences a logarithmic difference of the form $\log(v_t/v_{t-1})$ is used. Table 2.8 shows some descriptive statistics of non-transformed variables.

---

[19] Other measures for centrality such as betweeness-centrality or degree centrality have been used but dropped for collinearity reasons.

[20] An alternative measure for a banks centrality is the debtrank proposed by Battiston et al. (2012*c*).

Tables 2.9 and 2.10 show the correlation matrices of the variables used in the regression models and shows that no confounding effects from collinearity are to be expected. Each liability exposure that ever existed between two counter parties is reported in every time period and is zero when no actual exposure exists. As all of the data is audited and the dataset contains the entire population of banks in Germany, outliers were treated conservatively. Only banks with negative equity values are excluded from the analysis.[21]

In order to identify the differences between bank behaviour, a traditional diff-in-diff model (Abadie, 2005; Ashenfelter and Card, 1985; Card and Krueger, 1994) is used. The interaction effects of the diff-in-diff dummy D_i for a given bank type and the explanatory variables liquidity need ($D \times \theta$) and changes of the G &Y indicator ($D \times \Delta\psi$) provide the differential effect of a specific bank type. The OLS regressions control for bank fixed effects by demeaning as well as for time fixed effects by the inclusion of time dummy variables. A Hausman test shows conclusively that the within fixed effects model is to be preferred to a random effects model, which is in line with the theoretical understanding of differences in business models of banks.[22] To be precise, the following model is estimated:

$$(\phi_{it}-\bar{\phi_i}) = \boldsymbol{b_0}(\mathbf{x}_{it}-\bar{\mathbf{x}_i})+\boldsymbol{b_1}D_i\times(\mathbf{x}_{it}-\bar{\mathbf{x}_i})+\boldsymbol{b_2}(\mathbf{z}_{it}-\bar{\mathbf{z}_i})+\mathbf{T}_t+\mathbf{T}_t\times D_i+(\epsilon_{it}-\bar{\epsilon_i}), \quad (2.9)$$

where $\mathbf{x}_{it}$ is the vector of explanatory variables θ_{it} and ψ_{it}, $\mathbf{z}_{it}$ the vector of control variables, $\mathbf{T}_t$ a vector with dummy variables for time periods, and D_i the dummy variable indicating whether a bank is a member of the banking group of interest, and $\mathbf{b_j}$ for $j = 0, 1, 2$ the estimated parameters. The same model is used to estimate the

---

[21] Only a few of those cases exist in the dataset. If a bank goes bankrupt it is often still required to report to the Deutsche Bundesbank, which explains occasional negative entries for equity.

[22] The result of the Hausman test is a $\mathcal{X}^2 = 304.41$.

effect of the 2007/2008 financial crisis by including an additional dummy identifying the post-crisis period in addition to the interaction effect with explanatory variables.

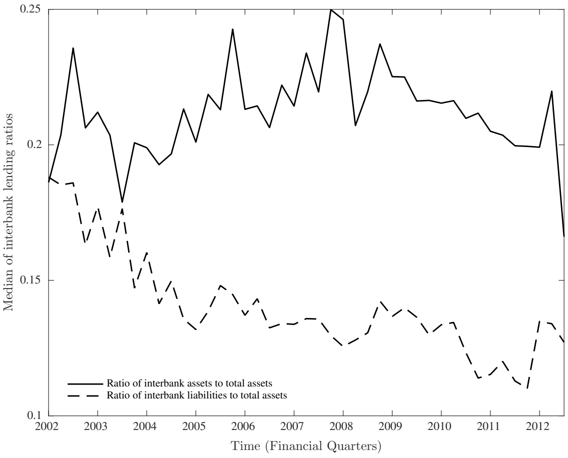
All analysis has been conducted using Stata 12 on premises of the Deutsche Bundesbank. To estimate the confidence interval of coefficients, a robust non-parametric estimator is used.

2.4 Results

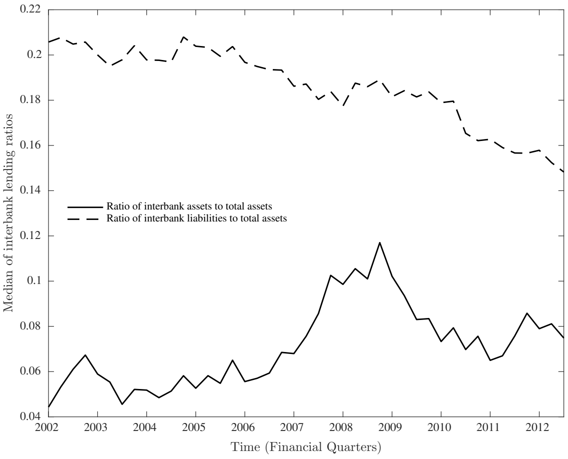
We first show that universal banks in Germany are predominantly not only lenders or borrowers in the interbank market, but both. Moreover, we briefly describe the evolution of the G&Y β, leverage, and asset and liability ratios for the different bank groups in Germany. We then show that interbank market activities of private banks in Germany do indeed correlate with changes in the bailout probability of banks. Moreover, we show that for private commercial banks the liquidity management function is much less important than for savings banks and credit cooperatives. Lastly, it is shown that these results are not affected by the 2007/2008 financial crisis.

Table 2.2 shows the distribution of the proportion of interbank assets and liabilities of the overall balance sheet size, as well as the balance between the two. While it is clear that the distribution of the proportion of interbank asset and liabilities of total asset (A_i^{IB}/A_i and L^{IB}/A_i respectively) is highly dispersed among banks of the same type, some simple insights can be gained. Banks neither tend to be just borrowers nor just lenders. This insight follows from the ratio between interbank assets and interbank liabilities in Table 2.2. Private commercial banks and credit cooperatives both have more balanced lending to borrowing ratios than savings banks. Of course, banks fulfil an intermediation role (cf. Farboodi, 2014) as noted above. If banks channel excess funding to profitable investment opportunities through intermediation

a) Private commercial banks



b) Savings banks



c) Credit cooperatives

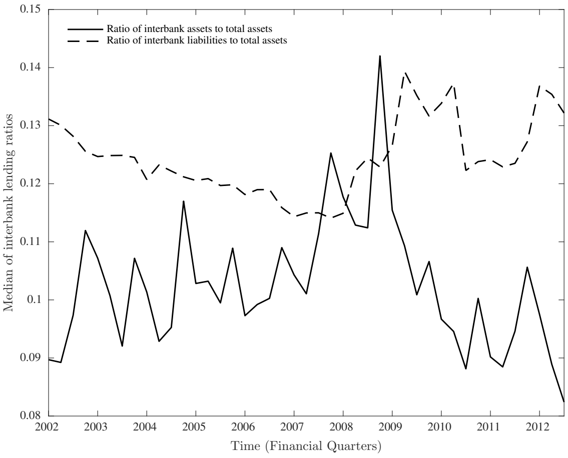


Figure 2.3: Evolution of interbank assets and liabilities ratios

The figure shows the evolution of the median ratio of interbank assets (liabilities) to total assets between 2002 and 2012 for three types of universal credit banks in Germany. Source: Created by author, based on Monatliche Bilanzstatistik, Deutsche Bundesbank, April 2014.

Bank type		$\frac{A_i^{IB}}{A_i}$	$\frac{L_i^{IB}}{A_i}$	$\frac{\min\{L_i^{IB}, A_i^{IB}\}}{\max\{L_i^{IB}, A_i^{IB}\}}$
Private commercial banks	median	0.21	0.14	0.35
(n=5767)	IQR	0.32	0.27	0.59
Savings banks	median	0.07	0.19	0.36
(n=17822)	IQR	0.07	0.13	0.43
Credit cooperatives	median	0.10	0.12	0.52
(n=46546)	IQR	0.09	0.08	0.42
Foreign commercial banks	median	0.47	0.73	0.54
(n=1501)	IQR	0.53	0.33	0.61
Other banks	median	0.11	0.12	0.48
(n=1668)	IQR	0.09	0.08	0.42

Table 2.2: Characteristic interbank lending ratios in Germany

The table shows the distribution of characteristic interbank lending and borrowing ratios for different bank types. The first column shows the interbank asset ratio, the second the interbank liability ratio. Both are calculated as a ratio of balance sheet size. The third column gives an indication of the balance between interbank assets and liabilities of a bank. Source: Created by author, based on Monatliche Bilanzstatistik, Deutsche Bundesbank, April 2014.

chains it is to be expected that at least some banks will have both high levels of interbank assets and liabilities.

Generally, it must be noted that interbank lending and borrowing can make up for a large portion of the balance sheet, with private commercial banks showing much higher levels of both lending and borrowing than other universal banks. Figure 2.3 further shows the evolution of interbank assets and liabilities ratios ($\sum_{i \in B} A_i^{IB} / \sum_{i \in B} A^i$ and $\sum_{i \in B} L_i^{IB} / \sum_{i \in B} A^i$ respectively) for the different bank types (C, U, and S). Across all bank types, the level of interbank loans increased since 2002 until the 2008 financial crisis and decreased significantly thereafter. This drop is more pronounced for savings banks and credit cooperatives. On the other hand, the ratio of interbank liabilities declined slightly over time, but rose significantly for credit cooperatives since the financial crisis.

Figure 2.4 shows the median ψs for the three bank types, while Figure 2.5 shows

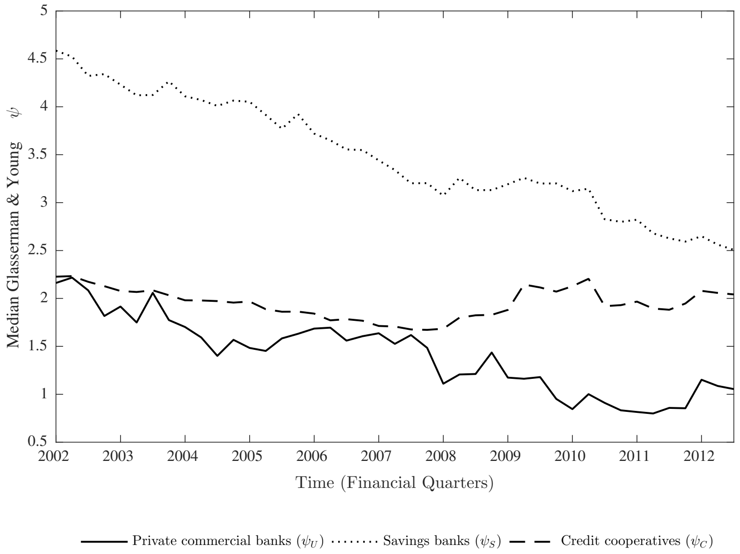


Figure 2.4: Glasserman & Young ψ for German universal banks 2002-2012

The graph shows median ψs for different bank types in Germany. ψ is calculated as in Eq. 2.4. The graph distinguishes private commercial banks, savings banks, and credit cooperatives. Source: Created by author, based on Monatliche Bilanzstatistik, Deutsche Bundesbank, November 2013.

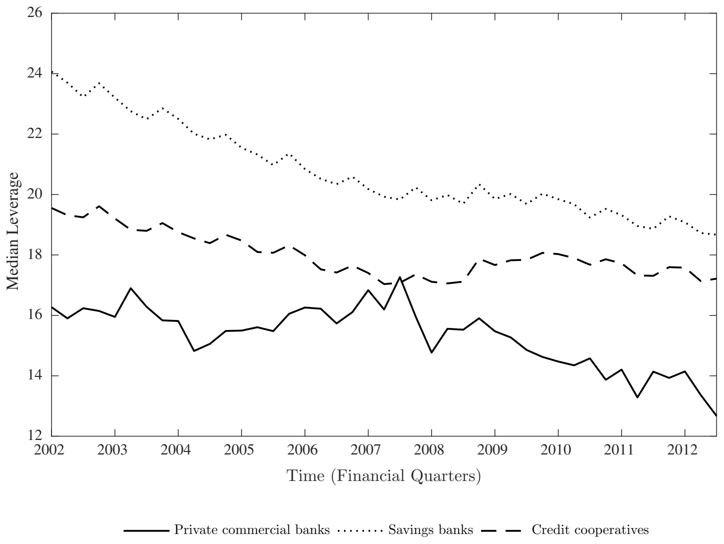


Figure 2.5: Leverage for German universal banks 2002-2012

The graph shows median leverage ratios (Total Assets / Equity) for different banking groups in Germany. Source: Created by author, based on Monatliche Bilanzstatistik, Deutsche Bundesbank, November 2013.

leverage ratios. For private commercial banks leverage ratios stayed at similar levels up to the financial crisis with a sudden drop during 2008 and a steady decline since. The G&Y ψ peaks in 2009 and drops afterwards. Generally it declines steadily over time. For savings banks and credit cooperatives we see a decline in leverage ratios up to 2008, which stayed steady since. The G&Y ψ for credit cooperatives is stable while decreasing slightly over time for savings banks. Comparing between the different bank types, ψs between private commercial banks and savings banks have been comparable in 2002, in 2012 private commercial bank ψs are closer to credit cooperatives. While the ψs of savings banks are always higher than those for credit cooperatives, their medians declined roughly in tandem up to the financial crisis and since then are converging. Thus, while there are some differences between the universal bank types, which are controlled for in all regressions by including bank fixed effect, savings banks, credit cooperatives, and private commercial banks are comparable. It is clear from Table 2.2 that foreign commercial banks are structured differently. Interbank liabilities make up for the largest proportion of the liabilities of these banks. They are thus excluded from the regression models on which the following results are based.

2.4.1 Effect of interbank market activity on systemic importance for private banks

Amongst universal banks, two types of private banks exist that are not directly or indirectly publicly owned: credit cooperatives and private commercial banks. The description of the interbank market above shows that commercial banks are structurally different from the other two. However, savings banks and credit cooperatives are comparable. Therefore, in order to identify whether the activities of private banks in the interbank market influence their bailout probability, the estimated model including

Coefficients of diff-in-diff model of change in net liabilities to other banks (Φ)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Independent variables							
Liquidity need (θ)	5.16***	6.1***	6.07***	6.32***	6.08***	6.32***	6.68***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Change of G&Y indicator ($\Delta\Psi$)	0.34***	-0.13	-0.12	-0.12	-0.12	-0.12	-0.22*
	(0.000)	(0.152)	(0.192)	(0.199)	(0.192)	(0.185)	(0.018)
Liquidity need (θ) x	-0.74	-0.21	-0.23	-0.45	-0.21	-0.45	-0.74
Credit cooperative dummy	(0.217)	(0.745)	(0.729)	(0.453)	(0.75)	(0.453)	(0.211)
Change of G&Y indicator ($\Delta\Psi$) x	0.42***	0.49***	0.48***	0.47***	0.47***	0.47***	0.49***
Credit cooperative dummy	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Control variables							
Change of other assets (ΔA_o)		1.88***	1.89***	1.9***	1.9***	1.9***	2.17***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Change of other liabilities (ΔL_o)		-0.83***	-0.82***	-0.82***	-0.83***	-0.82***	-0.7***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bank size (A)			-0.1***	-0.1***	-0.1***	-0.1***	-0.04***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage (A/w)			-0.06**	-0.06**	-0.06**	-0.06**	-0.14***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Change of equity (Δw)							-1.35***
							(0.000)
Change of intragroup lending				0.0***		0.0***	0.0***
(ΔG)				(0.000)		(0.000)	(0.000)
Centrality in interbank market				-0.04	0.0	-0.01	-0.01
(C_e)				(0.118)	(0.833)	(0.542)	(0.662)
Change of creditor/debtor ratio						-0.03	-0.02
(ΔR)						(0.108)	(0.326)
Time FE (not shown)							
Time x Credit cooperative dummy FE (not shown)							
Bank FE (not shown)							
Observations	62590	62590	62590	61360	61460	61460	61460
Number of groups	1632	1632	1632	1617	1617	1617	1617
Error Standard Deviation	0.49	0.46	0.46	0.46	0.46	0.46	0.45
Fixed-effect variance	0.02	0.02	0.08	0.09	0.09	0.09	0.03
Goodness of Fit (adj.)	0.17	0.28	0.28	0.28	0.28	0.28	0.29
F-Statistic (all coeff=0)	53.14	52.93	52.25	50.01	51.05	49.9	48.6

Legend: coefficient/(p-value); * $p < 0.05$,** $p < 0.01$, *** $p < 0.001$

Table 2.3: Main model for effect of credit cooperatives

The regression table shows coefficients and p-values for several diff-in-diff models estimated for all savings banks and credit cooperatives. They regress net liabilities to other banks on two independent variables and some bank-level control variables. The models include interaction effects for credit cooperatives and the explanatory variables in order to analyse whether credit cooperatives show different effects to savings banks. Where appropriate, variables are log-differences and a robust non-parametric estimator is used to calculate standard errors. Change in net liabilities to other banks is interperiod change of net interbank borrowing. Liquidity need is the difference of interperiod changes in loans and interperiod changes in deposits. The G&Y indicator gives an indication of the importance of a bank to the financial system. Control variables account for bank size and leverage, its position in the interbank market, and changes to the balance sheet that would mechanically change net liabilities to other banks. All models control for bank fixed effects, time fixed effects, and time-dummy interaction effects from the diff-in-diff model. Data sources: Monatliche Bilanzstatistik and Millionenevidenzdaten (both from Deutsche Bundesbank).

Coefficients of diff-in-diff model of change in gross short-term interbank liabilities (Φ'_{ST})						
	(1)	(2)	(3)	(4)	(5)	(6)
Independent variables						
Change of interbank assets (ΔA_{IB})	0.02***	0.03***	0.03***	0.03***	0.03***	0.03***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Liquidity need (θ)	0.28**	0.28***	0.29***	0.27***	0.29***	0.27***
	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Change of G&Y indicator ($\Delta\Psi$)	0.17***	0.14***	0.13***	0.13***	0.14***	0.14***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Liquidity need (θ) x	-0.33**	-0.24**	-0.23**	-0.2*	-0.21**	-0.2*
Credit cooperative dummy	(0.001)	(0.002)	(0.003)	(0.01)	(0.006)	(0.01)
Change of G&Y indicator ($\Delta\Psi$) x	0.16***	0.16***	0.16***	0.15***	0.14***	0.14***
Credit cooperative dummy	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Control variables						
Change of other assets (ΔA_o)		0.16***	0.16***	0.17***	0.17***	0.17***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Change of other liabilities (ΔL_o)		0.11***	0.11***	0.11***	0.11***	0.11***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bank size (A)			0.04***	0.04***	0.04***	0.04***
			(0.000)	(0.000)	(0.000)	(0.000)
Leverage (A/w)			0.0	0.0	0.0	0.0
			(0.897)	(0.919)	(0.927)	(0.896)
Change of intragroup lending				0.0*		0.0**
(ΔG)				(0.013)		(0.008)
Centrality in interbank market				0.02***	0.0	0.0
(C_e)				(0.000)	(0.759)	(0.434)
Change of creditor/debtor ratio						0.01
(ΔR)						(0.114)
Time FE (not shown)						
Time x Cooperative bank dummy FE (not shown)						
Bank FE (not shown)						
Observations	62560	62560	62560	61330	61430	61430
Number of groups	1632	1632	1632	1617	1617	1617
Error Standard Deviation	0.1	0.1	0.1	0.1	0.1	0.1
Fixed-effect variance	0.07	0.05	0.24	0.24	0.24	0.24
Goodness of Fit (adj.)	0.24	0.27	0.27	0.27	0.27	0.27
F-Statistic (all coeff=0)	32.24	33.16	36.24	38.6	35.29	37.43

Legend: coefficient/(p-value); * $p < 0.05$,** $p < 0.01$, *** $p < 0.001$

Table 2.4: Main model for gross short-term liabilities and credit cooperatives

The regression table shows coefficients and p-values for several diff-in-diff models estimated for all savings banks and credit cooperatives. They regress gross short-term liabilities to other banks on two independent variables and some bank-level control variables. Models include interaction effects for credit cooperatives and the explanatory variables in order to analyse whether credit cooperatives show different effects to savings banks. Where appropriate, variables are log-differences and a robust non-parametric estimator is used to calculate standard errors. Liquidity need is the difference of interperiod changes in loans and interperiod changes in deposits. The G&Y indicator gives an indication of the importance of a bank to the financial system. Control variables account for bank size and leverage, its position in the interbank market, and changes to the balance sheet that would mechanically change liabilities to other banks. All models control for bank fixed effects, time fixed effects, and time-dummy interaction effects from the diff-in-diff model. Data sources: Monatliche Bilanzstatistik and Millionenevidenzdaten (both from Deutsche Bundesbank).

a dummy for credit cooperatives allows one to estimate the relationship between the G&Y indicator ($\Delta\psi$) and net interbank borrowing (θ) attributable to being a private bank.

Table 2.3 shows the results of this analysis. Model (1) shows a strongly significant correlation between a change in the G&Y indicator of the baseline model for savings banks. When introducing control variables (Models 2 to 7), the direction of the effect is preserved, even though it is not always significant. For savings banks, the interbank market activity shows a negative correlation with the bailout probability indicator, even though it is not always statistically significant. An increase in net borrowing would be associated with a reduction in the bailout probability, even if small. However, for credit cooperatives one can identify a strongly significant and positive correlation between net interbank borrowing and the indicator. This effect is in excess of the negative effect of the baseline established by savings banks and stable with the introduction of different control variables, as well as estimating the same model but with a savings bank dummy (cf. Table 2.11). Thus, for private banks with uninsured liabilities, interbank market activities are associated with a change in the bailout probability proxy. One can therefore conclude that in addition to the liquidity management function, the interbank market also fulfils a strategic bailout probability management function.

Table 2.12 in Appendix C shows that the described effect is also present when analysing short-term net interbank borrowing only. Moreover, when comparing all universal banks (cf. Table 2.5), the effect is preserved too. Throughout all models in which credit cooperatives and savings banks are used to establish a benchmark, a highly significant and positive effect exists for private commercial banks. That is, even in excess of the higher benchmark established by credit cooperatives, for commercial banks the correlation between a higher bailout probability and an increase in net interbank borrowing is stronger.

The effect is also present when analysing gross interbank borrowing. Table 2.4 estimates several models for gross short-term interbank borrowing and controls include changes in short-term interbank assets. Interestingly, an increase in short-term interbank borrowing is positively correlated to short-term interbank lending, even though the effect is small. While the G&Y indicator is positively correlated with interbank borrowing, the additional effect for credit cooperatives is still strongly significant and positive.

In summary, the evidence provided by the German interbank market is consistent with hypothesis H2. For private banks, a distinct positive effect exists between an increase in liabilities to other banks and an increase in the bailout probability proxy beyond the effect expected by a peer group. The effect is present for credit cooperatives in direct comparison with savings banks, a stronger effect is present for private commercial banks when using savings banks and credit cooperatives as a baseline, and it is preserved at different maturities and when estimating interbank borrowing in gross terms.

2.4.2 Liquidity management secondary driver for private commercial banks

Throughout all models, a highly significant and positive correlation can be found between net interbank borrowing and the liquidity needs of banks. This is consistent with hypothesis H1a and with the standard assumption of economic literature. The effect is strongest when considering total net interbank borrowing (cf. Tables 2.3 and 2.5) but also present in models for net short-term borrowing (cf. Table 2.12) and

Coefficients of diff-in-diff model of change in net liabilities to other banks (Φ)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Independent variables							
Liquidity need (θ)	4.6***	5.21***	5.18***	5.33***	5.32***	5.32***	5.34***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Change of G&Y indicator ($\Delta\Psi$)	0.67***	0.49***	0.5***	0.45***	0.45***	0.45***	0.43***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Liquidity need (θ) x	-4.47***	-4.99***	-4.96***	-5.13***	-5.11***	-5.11***	-5.13***
Private commercial bank dummy	(0.000)	(0.000)	(0.000)	(0.000)	(0.00)	(0.000)	(0.000)
Change of G&Y indicator ($\Delta\Psi$) x	0.25**	0.39***	0.38***	0.36**	0.38**	0.38**	0.39**
Private commercial bank dummy	(0.001)	(0.000)	(0.000)	(0.005)	(0.001)	(0.001)	(0.001)
Control variables							
Change of other assets (ΔA_o)		0.8***	0.8***	0.98***	0.98***	0.98***	1.02***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Change of other liabilities (ΔL_o)		-0.5***	-0.49***	-0.57***	-0.58***	-0.58***	-0.55***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bank size (A)			-0.04**	-0.06***	-0.06***	-0.06***	-0.04**
			(0.008)	(0.000)	(0.000)	(0.000)	(0.001)
Leverage (A/w)			-0.11***	-0.1***	-0.09***	-0.09***	-0.12***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Change of equity (Δw)							-0.26
							(0.133)
Change of intragroup lending				0.0		0.0	0.0
(ΔG)				(0.152)		(0.148)	(0.17)
Centrality in interbank market				-0.02	0.04	0.03	0.04
(C_e)				(0.63)	(0.105)	(0.301)	(0.191)
Change of creditor/debtor ratio						-0.01	-0.01
(ΔR)						(0.406)	(0.436)
Time FE (not shown)							
Time x Cooperative bank dummy FE (not shown)							
Bank FE (not shown)							
Observations	67451	67449	67449	64612	64885	64885	64885
Number of groups	1885	1885	1885	1749	1753	1753	1753
Error Standard Deviation	0.51	0.49	0.49	0.48	0.48	0.48	0.48
Fixed-effect variance	0.08	0.09	0.11	0.09	0.09	0.09	0.08
Goodness of Fit (adj.)	0.26	0.3	0.3	0.26	0.27	0.27	0.27
F-Statistic (all coeff=0)	53.0	55.56	56.12	54.25	56.24	55.17	53.76

Legend: coefficient/(p-value); * $p < 0.05$,** $p < 0.01$, *** $p < 0.001$

Table 2.5: Main model for effect of private commercial banks

The regression table shows coefficients and p-values for several diff-in-diff models estimated for all universal credit banks in Germany. They regress net liabilities to other banks on two independent variables and some bank-level control variables. The models include interaction effects for private commercial banks and the explanatory variables in order to analyse whether private commercial banks show different effects to other universal banks. Where appropriate, variables are log-differences and a robust non-parametric estimator is used to calculate standard errors. Change in net liabilities to other banks is interperiod change of net interbank borrowing. Liquidity need is the difference of interperiod changes in loans and interperiod changes in deposits. The G&Y indicator gives an indication of the importance of a bank to the financial system. Control variables account for bank size and leverage, its position in the interbank market, and changes to the balance sheet that would mechanically change net liabilities to other banks. All models control for bank fixed effects, time fixed effects, and time-dummy interaction effects from the diff-in-diff model. Data sources: Monatliche Bilanzstatistik and Millionenevidenzdaten (both from Deutsche Bundesbank).

gross short-term borrowing (cf. table 2.4). For the more regionally-focused savings banks and credit cooperatives no significant differences between the two banking groups can be found consistently. Only for short-term gross borrowing is the effect slightly smaller for credit cooperatives than for savings banks. The role of banks to channel funds to profitable investment opportunities manifests itself in the same way as liquidity co-insurance does. Banks may borrow in the interbank market in order to take advantage of profitable lending opportunities which leads to intermediation chains.

However, consistent with hypothesis H1b, the correlation between net interbank borrowing and liquidity needs is much smaller for private commercial banks (cf. Table 2.5). In fact, ignoring any control variables model (1) of Table 2.13 shows no significant positive correlation at all. While not statistically significant, the effect for liquidity management is also muted for credit cooperatives (cf. Table 2.3). Thus, while a strong correlation between the indicator for strategic behaviour is present in the data, for private commercial banks the changes in interbank liabilities are much less determined by liquidity needs.

2.4.3 Stability throughout financial crisis and effects of controls

Table 2.6 shows models examining the effect of the financial crisis on the explanatory variables. The dummy variable included for post-crisis is for all time periods after October 2008. The models include both a dummy for post-crisis as well as interaction effects with the explanatory variables. While there is a very small positive effect on net interbank borrowing in post-crisis periods, no significant effects on either the liquidity provision effect or the G&Y indicator are found. The absence of any such effects suggests that the identified effects are stable.

Coefficients of diff-in-diff model of change in net liabilities to other banks (Φ)				
	(1)	(2)	(3)	(4)
Independent variables				
Liquidity need (θ)	0.5**	0.58***	0.57***	0.81**
	(0.001)	(0.000)	(0.000)	(0.001)
Change of G&Y indicator ($\Delta\Psi$)	0.86***	0.8***	0.81***	0.8***
	(0.000)	(0.000)	(0.000)	(0.000)
Post-crisis dummy	0.15***	0.14***	0.04*	0.07***
	(0.000)	(0.000)	(0.021)	(0.000)
Liquidity need (θ) x	-0.24	-0.19	-0.18	-0.42
Post-crisis dummy	(0.077)	(0.219)	(0.227)	(0.065)
Change of G&Y indicator ($\Delta\Psi$) x	0.05	0.03	0.03	-0.08
Post-crisis dummy	(0.547)	(0.733)	(0.731)	(0.359)
Control variables				
Change of other assets (ΔA_o)		0.67***	0.67***	0.82***
		(0.000)	(0.000)	(0.000)
Change of other liabilities (ΔL_o)		-0.39***	-0.38***	-0.44***
		(0.000)	(0.000)	(0.000)
Bank size (A)			-0.05**	-0.07***
			(0.002)	(0.000)
Leverage (A/w)			-0.15***	-0.15***
			(0.000)	(0.000)
Centrality in interbank market				0.02
(C_e)				(0.438)
Time FE (not shown)				
Time x Cooperative bank dummy FE (not shown)				
Bank FE (not shown)				
Observations	67451	67449	67449	64885
Number of groups	1885	1885	1885	1753
Error Standard Deviation	0.52	0.51	0.51	0.5
Fixed-effect variance	0.07	0.08	0.11	0.09
Goodness of Fit (adj.)	0.22	0.24	0.24	0.2
F-Statistic (all coeff=0)	62.99	68.62	68.03	66.8

Legend: coefficient/(p-value); * $p < 0.05$,** $p < 0.01$, *** $p < 0.001$

Table 2.6: Effect of financial crisis on interbank market activity

The regression table shows coefficients and p-values for several diff-in-diff models estimated for all universal credit banks in Germany. They regress net liabilities to other banks on two independent variables and some bank-level control variables. The models include a dummy variable for post-financial crisis periods (post Q3 2008) and interaction effects of the dummy and the explanatory variables to analyse whether the financial crisis had an effect on interbank market behaviour. Where appropriate, variables are log-differences and a robust non-parametric estimator is used to calculate standard errors. Change in net liabilities to other banks is interperiod change of net interbank borrowing. Liquidity need is the difference of interperiod changes in loans and interperiod changes in deposits. The G&Y indicator gives an indication of the importance of a bank to the financial system. Control variables account for bank size and leverage, its position in the interbank market, and changes to the balance sheet that would mechanically change net liabilities to other banks. All models control for bank fixed effects, time fixed effects, and time-dummy interaction effects from the diff-in-diff model. Data sources: Monatliche Bilanzstatistik and Millionenevidenzdaten (both from Deutsche Bundesbank).

The analysis focuses on explaining the dynamic behaviour of banks in the interbank market. Throughout the regression models the adjusted goodness of fit is less than 0.3. A low goodness of fit is not surprising, given much of the lending and borrowing decisions arise out of the bilateral relationship between banks and depend on individual bank characteristics such as riskiness, credit rating, prior lending history, or the position in the interbank market, which cannot be included in this study. The regression models control for these effects through bank fixed effects (as well as time fixed effects), which are not shown in the output.

The regression models control for a range of variables that are expected to mechanically influence the size of net interbank liabilities as well as for bank-specific characteristics such as leverage and the position of a bank in the interbank market, which similarly can be expected to have an effect on the size of changes in net liabilities to other banks. Due to the balance sheet identity, one would expect an increase of assets or a decrease in non-interbank liabilities to lead to an increase in net liabilities to the interbank market. All models therefore control for changes in bank size by including effects for changes in other assets, other liabilities, and equity. When those coefficients are statistically significant, one obtains coefficients of expected directionality. When other assets increase, net interbank borrowing increases, while when other liabilities increase, net interbank borrowing decreases. Changes in equity are negatively correlated with changes in net interbank liabilities.

In order to account for the tiering of the German interbank market as identified by Craig and von Peter (2014), who show that large banks occupy core positions in the interbank market, all models also control for the absolute size of banks, as well as their leverage. Models four to seven always control for positional factors as well as changes in interbank exposures potentially attributable to a change in the composition of borrowers and lenders ΔR, and changes in the complexity of bank operations (as proxied by ΔG i.e. the lending among independent entities of the same bank). Generally, the centrality of a bank in the interbank market C_i^e does not have a statistically significant effect on the dynamic evolution of liabilities over time for any bank type. There is a small negative effect for short-term interbank borrowing. Changes in the balance of creditor to debtors (ΔR_i) are not statistically significant. The level of intragroup lending (G_i) and leverage (A_i/w_i) are further indicators for the size and complexity of the operations of a bank and thus included as controls.

2.5 Discussion

This is the first study that empirically examines the factors contributing to the emergence of interbank markets. Isolating an additional driver for private banks to be active in the interbank market is the main contribution of our work. In addition to managing liquidity needs, the interbank market activities of private banks influence their bailout probability. The study identifies a strong relationship between an increase in liabilities to other banks and an increase in the G&Y indicator, which is used as a proxy for the bailout probability of a bank, attributable purely to the governance structure of private banks. The study further shows that the liquidity management function of the interbank market is less important for private commercial banks than it is for more regionally-oriented banks. While models considering idiosyncratic liquidity shocks as the rationale for interbank lending may adequately represent a subclass of banks, at least for some types of banks further incentives need to be considered. The finding is in line with differences in the business models of different bank types active in the German interbank market. We discuss the limitations of the study before addressing implications for economic theory and policy makers.

The study has at least three limitations. Firstly, we could not test whether the G&Y indicator is a proxy for the probability that an insolvent entity would receive guarantees or any form of tangible economic advantage. Follow-up work should address whether the G&Y indicator and other structural measures of importance to the financial system influence the return on assets by banks. Credit rating agencies offer two types of credit ratings, standalone credit ratings as well as 'all-in' credit ratings including support ratings (King, Ongena and Tarashev, 2016). Standalone ratings consider only the financial strength of an institution. Support ratings offer a view on the likelihood that in case of need liabilities will be guaranteed. Such support is likely to stem from governments. Thus, support ratings could be used as an additional measure of systemic importance. In addition, the difference in credit ratings between standalone and support ratings could be taken as a measure of economic benefit from higher bailout probabilities.

It seems plausible that the systemic importance of banks has a bearing on the bailout probability, or at least the perceived bailout probability. This effect in return ought to reduce borrowing costs of banks which would constitute a sufficient driver of interbank borrowing. Several studies have examined a natural experiment in Germany, in which explicit government guarantees for Landesbanken were abolished (cf. Fischer et al., 2014, Gropp, Gruendl and Guettler, 2014, and Körner and Schnabel, 2013). Landesbanken are large credit-centre banks for savings banks. The studies conclusively establish a loss of economic value due to the removal of explicit guarantees that manifests itself in increased bond spreads, higher funding costs, lower credit ratings, and a loss of charter value. At the same time the studies show that a removal of guarantees induced higher risk-taking, which is in line with our findings.

Acharya, Anginer and Warburton (2015) provide further evidence for the effect of implicit government guarantees on borrowing costs. They find that for the largest financial institutions in the US credit spreads are not sensitive to idiosyncratic risk measures.

Future work further needs to examine how governments decide on whether to bail out banks. Regulators generally face a trade-off between assuring depositors of the safety of their deposits, and thus avoid bank runs, and ensuring that banks do not engage in excessive risk taking (Shapiro and Skeie, 2015). Bank runs as well as excessive risk taking pose a source of systemic risk. It seems plausible that bail out decisions are driven by two factors and motivated by ensuring a functioning banking system. If the overall stability of the financial system is large or the failure of a bailout candidate is likely to not cause contagious effects, regulators are more likely to not bail out banks but rather increase deposit guarantees. Similarly, if uncertainty is high and the banking system under pressure, for instance due to asset depreciations, bail outs may be more likely.

Secondly, while the dataset offers detailed information on the balance sheets of banks and bilateral exposures, the granularity of this information is limited both in the sense that it does not include any information about individual loans, but also in that it only shows quarterly data. In any study of this type, some uncertainty regarding the liquidity needs, the level of interbank lending, and the level of interbank borrowing remain. Bluhm, Georg and Krahnen (2016) further explore questions of interbank intermediation in the German interbank market. While the dataset allows one to differentiate between loans of different maturities, no daily information on either bilateral exposures nor balance sheets exists. Of course markets exist to balance out shortfall and excess liquidity in federal fund reservers in order to meet minimum reserve requirements. Afonso, Kovner and Schoar (2011) study this market and show that bank characteristics become more important in times of financial distress and that long-standing lending and borrowing relationships help to limit borrowing costs. The results of this study thus cannot be taken to preclude that at short maturities private commercial banks are highly active in interbank markets to balance liquidity fluctuations. However, the muted liquidity management effect documented for private commercial banks and the heightened effect for a bailout probability indicator allow one to conclude that liquidity management, while an important driver of interbank markets, is not the only reason why banks enter interbank exposures.

Moreover, alternative sources for satisfying liquidity needs exist, especially for private commercial banks. These include bond markets, repo transactions, and raising further capital. While the study controls for changes in capital, credit markets and repo transactions are not included. For future research into the liquidity management of private commercial banks these sources of funds ought to be included.

Thirdly, the study only analyses the interbank market of one country. Therefore, it is impossible to estimate a function for the probability of bailout or market sentiments and take account of the fact that the importance and composition of interbank markets differ between countries. For instance, assume that the probability of government support of failing financial institutions was significantly lower in the US than in Germany, but the importance of banks to the financial system be evaluated in the same manner. It seems reasonable to assume a cost associated with increasing interbank exposures depending on bank characteristics such as size. For some banks, it would never be optimal to target a high G&Y indicator because irrespective of the structure of their balance sheet, deposits would not be guaranteed. It also seems reasonable to assume that there is some uncertainty or ambiguity regarding

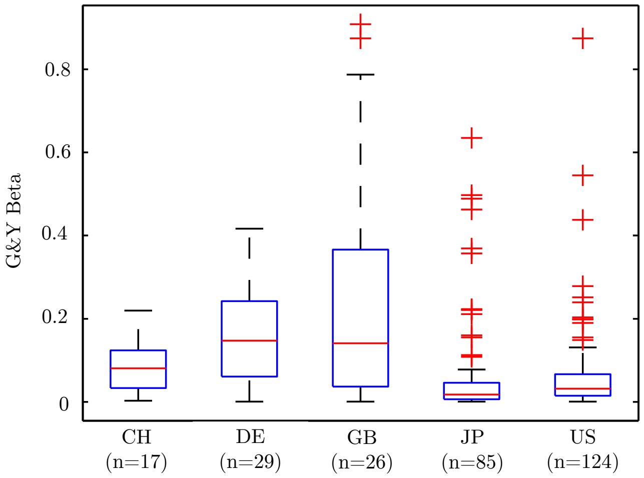


Figure 2.6: Intercountry comparison of Glasserman & Young βs 2012

The figure shows an intercountry comparison of the distribution of G&Y βs in 2012 by showing box plots for publicly traded banks in five different countries. Outliers of more than 1.5 interquartile ranges above Q3 or below Q1 are plotted separately. It considers only banks that are headquartered in the respective country in order to avoid data artefacts related to cross-country lending between subsidiaries and their parent bank. Source: created by author, data from Bankscope (2013).

the threshold at which a bank would receive government support.

With this framework in mind, one could account at least for some stylised facts as can be seen in the distributions of G&Y β_is between Germany and the US in 2012 (cf. Figure 2.6). It is clear from the plot that while a significant dispersion of β_is exists within countries, the distributions are fundamentally different between countries. If managing interbank exposures is associated with a cost, increasing them to a level sufficient for the market sentiment to tip towards expecting guarantees may be suboptimal. A dispersed distribution of β_is is always to be expected, given differences in the business models of financial institutions. In order to understand the role of different jurisdictions, comparative studies between countries are necessary. The model in Chapter 3 uses a bailout function for which two parameters can be estimated that characterise intercountry or temporal differences in the uncertainty that a bank with a given G&Y indicator would receive financial guarantees or a bailout as well as the threshold at which such aid would be granted. However, given the confidential nature of the data, as well as a limited number of countries with suitable data availability, this stream of research could prove difficult.

The chapter has some theoretical implications. First and foremost, banks show very different behaviour depending on their business model. So, in any banking models such structural and environmental characteristics need to be considered. Moreover, interbank markets do not serve a uniform purpose. One can distinguish between the liquidity management function, which is present for all banks but more pronounced for smaller banks with a regional focus, but moreover scholars need to explain a strategic function decoupled from the liquidity function. Others have argued that banks coordinate their behaviour in making investment decisions in order to fail together and benefit from ensuing government support (cf. Acharya and Yorulmazer, 2007; Eisert and Eufinger, 2013; Farhi and Tirole, 2012) and even that banks can shift systemic risk to governments by such coordinated behaviour (Acharya, 2009). In addition to becoming more connected through interbank lending, investing in the same assets causes indirect linkages between financial institutions that can act to further induce government subsidies. However, there is no evidence for banks colluding in order to extract a government subsidy, even though evidence exists of higher risk taking following government bailouts (Duchin and Sosyura, 2014). Instead, if market sentiments matter for the return expectations of investors and depositors, competitive banks have an individual incentive to increase their perceived importance to the financial system (lower borrowing cost). It is a well documented effect in sociology that status in markets matters for pricing structures of firms (cf. Podolny, 1993). Moreover, Podolny (2005) shows that status can be modelled through network centrality measures. Firms with higher status obtain a premium due to the signalling effect of status as conveying higher quality of intangible services. Market sentiments regarding the probability of default can play a similar role with regards to expected absolute returns. As the market sentiment is less important for savings banks due to having a deposit insurance scheme and public ownership, this line of reasoning offers an explanation for the observed findings.

The study also illustrates a dilemma for policy makers. Banks differ by their business model and thus regulation should be tailored specifically to structural and behavioural differences arising from that. While it is a trivial point that government behaviour will influence strategic decisions by banks, it is somewhat more subtle to think about the structural consequences this behaviour can have. The identification of strategic behaviour of universal banks and an additional driver of interbank markets provide a coherent explanation for why taxpayer-funded bank-bailouts create adverse incentives. For instance, establishing a formal mechanism in Europe to deal with bank defaults in order to avoid financial contagion in the case of collapse of an institution may exacerbate the underlying problem as opposed to solving it. It is commonly agreed that large financial institutions should not fail because of concerns that in a highly connected financial system such failures could lead to contagion (cf. Bhattacharya and Nyborg, 2013, Freixas et al., 2000, Freixas and Rochet, 2008, 2013, Gai, Haldane and Kapadia, 2011). Financial institutions act in a competitive environment. If market participants form expectations regarding the likelihood of bank bailouts based on some observable signal of a bank, either based on a structural measure or on a balance-sheet-based one, then any policy that lowers the bar for bank bailouts will lead to a more tight-knit financial system. As long as costs of increasing interbank liabilities are sufficiently low, higher interbank connections are beneficial to financial institutions. So, rather than discouraging a close-knit interbank market in the first place such policies may lead to an increase in interconnectivity.

Precisely this conundrum has been addressed in the 'Vickers report', which has had decisive influence in the reform of the UK banking sector (cf. HM Treasury, 2012). By ring fencing bank operations central to the real economy and allowing other parts of banks to fail in case of financial difficulty, some uncertainty regarding bailouts is removed. In Chapter 3 we show that in the absence of liquidity shocks, an uncertain positive probability of bailout needs to exist in order for an interbank market to emerge. As a consequence, if ring fencing can be enforced credibly, this reduces the likelihood of inflated interbank lending and thus reduces systemic risk in a banking system.

2.6 Conclusion

We have shown that the traditional assumption of interbank markets as a mechanism to balance out liquidity needs is incomplete and that additional drivers need to be taken seriously. While the empirical findings support the liquidity management function of interbank markets, for private banks the data supports a theory of interbank markets in which the liabilities to other banks influence the probability of being bailed out under financial distress. Moreover, for private commercial banks in Germany the relationship between liquidity needs and interbank market activities is much weaker than for its smaller and regionally-focused counterparts (savings banks and credit cooperatives). Thus, the results of the study indicate that the purpose of interbank market activity varies substantially for different types of banks and that banks with uninsured liabilities act strategically in the interbank market. This insight not only has implications for economic theory in that models of interbank lending need to account for bank type, but also that additional incentives for banks engaging in interbank lending need to be accounted for in theoretical models. The study thus supports a growing literature exploring alternatives to liquidity co-insurance as drivers of interbank markets.

2.7 Appendices

2.7.1 Appendix A: Descriptive statistics of the German banking sector and interbank market

Table 2.7 contains some key variables describing the German banking sector as well as the interbank market and shows their evolution between 2002 and 2012. It shows the size of the banking sector, total interbank liabilities, total equity, the number of banks, as well as total intragroup exposure and interbank exposure. The intragroup exposures are all on and off-balance sheet exposures between entities with the same parent bank. Total intragroup exposure is simply the sum of all credit and derivatives exposure (on and off-balance sheet exposures) of all entities with a banking license in Germany. In addition, the table contains some descriptive network variables. Each bank in the market is considered a node and each bilateral exposure is considered a weighted directed edge, where the weight is equivalent to total exposure. Three network measures are reported.[23]

1. Diameter (SCC): the diameter of the smallest connected component (SCC) is the longest shortest path between any two nodes in a network that are connected by a path. Say A, B, and C are banks. If A has an exposure to B and B has an exposure to C, then A and C are connected through a path of length two.

2. Average undirected clustering:[24] The network is reduced to an unweighted and undirected network. I.e. links between nodes are binary. If an exposure of one bank to another exists, the two are said to be linked or being connected by an edge. Clustering can be measured in different ways (cf. Newman, 2010). In this

---

[23] cf. Newman (2010) or Jackson (2008)

[24] Calculated using NetworkX library (Python), cf. https://networkx.github.io/documentation/latest/reference/generated/networkx.algorithms.cluster.average_clustering.html#networkx.algorithms.cluster.average_clustering [Accessed: 13 September 2015].

chapter we measure the extent to which two nodes that share a common link to a third node are also linked, often referred to as transitivity. Such a (potential) triangular relationship is called triplet. Clustering measures the ratio of existing triplets to potential triplets. We can define c_i as the clustering coefficient of a node in a network. In an undirected graph it is the number of triplets (T_i) passing through that node to the possible number of triplets passing through that node. Letting n be the number of nodes in a network, N the set of those nodes, and d_i the number of neighbours of node i (or the edges of node i), then clustering is

$$c_i = \frac{2T_i}{d_i(d_i - 1)} \tag{2.10}$$

and thus the average undirected clustering

$$C = \frac{1}{n} \sum_{i \in N} c_i. \tag{2.11}$$

3. Density: This is simply the ratio of the existing number of links in a network to possible links in a network. So, a low density means that a network is sparse and only very few of the possible links exist. Using the same nomenclature as above we can write density for a directed network as

$$D = \frac{\sum_{i=1}^{N} d_i}{n(n-1)}. \tag{2.12}$$

Period	Sector size (bnEUR)	Total interbank liabilities (bnEUR)	Total equity (bnEUR)	Active banks	Number of bilateral domestic exposures	Total intragroup exposure (bnEUR)	Total interbank exposure (bnEUR)	Diameter (SCC)	Avg. undirected clustering	Density
200203	6349	1778	240	2177	25379	1567	1475	5	0.87	0.0054
200206	6320	1776	243	2137	25710	1509	1522	4	0.88	0.0056
200209	6382	1791	250	2060	25154	1426	1515	4	0.87	0.0059
200212	6452	1843	251	2059	25332	1432	1523	4	0.86	0.0060
200303	6470	1833	253	2036	25145	1408	1503	4	0.87	0.0061
200306	6511	1868	252	1986	24478	1384	1481	4	0.86	0.0062
200309	6442	1789	252	1960	25221	1292	1564	4	0.86	0.0066
200312	6471	1813	252	1958	25202	1280	1490	4	0.86	0.0066
200403	6543	1836	241	1956	25022	1275	1502	4	0.86	0.0065
200406	6587	1852	246	1936	25120	1287	1508	4	0.86	0.0067
200409	6633	1844	243	1911	24855	1262	1511	4	0.86	0.0068
200412	6664	1866	246	1909	25730	1330	1562	4	0.86	0.0071
200503	6768	1903	244	1905	25348	1421	1580	4	0.86	0.0070
200506	6893	1952	252	1889	24966	1527	1654	4	0.85	0.0070
200509	6913	1937	255	1856	24694	1586	1629	4	0.85	0.0072
200512	6903	1943	260	1856	24933	1583	1589	4	0.85	0.0072
200603	7041	1992	281	1850	23808	1685	1593	4	0.84	0.0070
200606	7109	2013	286	1836	23406	1624	1590	4	0.85	0.0069
200609	7113	1974	287	1816	22859	1568	1563	4	0.85	0.0069
200612	7188	2031	288	1816	22746	1601	1522	4	0.85	0.0069
200703	7320	2083	292	1807	22203	1752	1520	4	0.84	0.0068
200706	7410	2078	299	1806	21865	1853	1546	5	0.84	0.0067
200709	7533	2160	305	1798	21743	1663	1556	4	0.83	0.0067
200712	7626	2211	306	1792	21961	1703	1590	4	0.83	0.0068

continued...

Period	Sector size (bnEUR)	Total interbank liabilities (bnEUR)	Total equity (bnEUR)	Active banks	Number of bilateral domestic exposures	Total intragroup exposure (bnEUR)	Total interbank exposure (bnEUR)	Diameter (SCC)	Avg. undirected clustering	Density
200803	7696	2217	315	1791	21702	1728	1623	4	0.84	0.0068
200806	7745	2211	311	1777	22432	1916	1729	4	0.83	0.0071
200809	7954	2337	319	1760	22403	2058	1732	4	0.83	0.0072
200812	7956	2278	332	1760	22614	2152	1701	4	0.84	0.0073
200903	7840	2154	330	1753	22426	2213	1672	4	0.84	0.0073
200906	7772	2181	335	1740	22258	2073	1624	4	0.84	0.0074
200909	7592	2039	336	1713	22180	1965	1620	4	0.85	0.0076
200912	7510	2001	343	1719	22521	1905	1520	4	0.85	0.0076
201003	7528	2023	332	1711	22598	1968	1584	4	0.85	0.0077
201006	7924	2138	330	1715	22692	2057	1664	5	0.85	0.0077
201009	7691	1968	331	1704	22323	1972	1587	5	0.84	0.0077
201012	8458	1973	344	1704	22322	2158	1784	4	0.84	0.0077
201103	8104	1881	349	1710	22377	2062	1721	4	0.84	0.0077
201106	8036	1805	349	1708	22070	2028	1673	4	0.83	0.0076
201109	8638	1915	351	1694	22059	2096	1713	5	0.83	0.0077
201112	8560	1859	353	1692	22088	2052	1702	5	0.83	0.0077
201203	8694	2110	354	1693	22237	2003	1690	5	0.82	0.0078
201206	8806	2049	354	1694	22023	2056	1724	5	0.82	0.0077
201209	8735	1985	357	1681	21741	2022	1706	5	0.82	0.0077

Table 2.7: Evolution of some key variables of the interbank market

2.7.2 Appendix B: Description of key variables and correlation matrices

Table 2.8 shows descriptive statistics for some of the original variables in the dataset at different points in time. It shows that all variables are asymmetrically distributed. This is reflective of a tiered banking system with some very large banks and many small institutions. For the regression analyses variables are largely log-transformed.

Table 2.9 shows the correlation coefficients between the variables used for the regression analyses presented in Table 2.3. Table 2.10 shows the correlation coefficients between the variables used for the regression analyses presented in Table 2.4. As a consequence of the transfomations the correlations between variables are mostly low, so that they cannot be expected to distort regression results.

Period	Statistic	Assets m EUR	Loans m EUR	IB liabilities m EUR	Deposits m EUR	Equity m EUR	IB exposure m EUR	Eigen-centrality	Beta	Leverage
200212	N	2253	2253	2253	2253	2253	2044	2044	2253	2238
	Sum	6450000	3020000	1840000	620000	251000	1520000			
	Mean	2863	1340	818	275	112	743	0.01	0.19	22.93
	SD	21000	9358	6961	1094	905	5729	0.02	0.15	47.68
	Skewness	13.4	16.5	14.7	17.3	17.7	14.1	19.0	2.8	32.4
	Kurtosis	205.3	352.9	242.4	375.1	369.2	230.0	490.4	13.6	1183.8
	IQR	755318	447768	141241	199281	33584	163550	0.00	0.11	6.12
200612	N	1941	1941	1941	1941	1941	1805	1805	1941	1926
	Sum	7190000	3060000	2030000	704000	288000	1520000			
	Mean	3703	1574	1046	363	148	843	0.01	0.18	21.31
	SD	26100	9551	8703	1970	1015	5991	0.02	0.16	52.76
	Skewness	12.9	13.3	14.4	21.7	14.1	13.9	18.2	2.9	38.0
	Kurtosis	192.8	223.4	235.7	576.5	232.3	234.1	441.9	13.4	1572.3
	IQR	952434	550119	157587	228712	46622	190658	0.01	0.12	5.78
200812	N	1871	1871	1871	1871	1871	1749	1749	1871	1849
	Sum	7960000	3230000	2280000	657000	332000	1700000			
	Mean	4252	1726	1218	351	177	972	0.01	0.18	22.50
	SD	30200	10200	9954	2014	1321	6238	0.02	0.15	106.41
	Skewness	12.8	11.9	14.7	19.6	14.7	13.0	17.8	2.8	41.8
	Kurtosis	188.9	169.3	258.9	460.1	243.9	207.3	421.7	13.3	1781.5
	IQR	1083388	595873	176884	201075	54752	285597	0.01	0.12	5.98
201112	N	1780	1780	1780	1780	1780	1680	1680	1780	1761
	Sum	8540000	3230000	1860000	765000	353000	1690000			
	Mean	4797	1813	1042	430	198	1008	0.01	0.17	21.69
	SD	44300	11200	10200	3110	1566	8219	0.02	0.15	75.47
	Skewness	20.7	14.4	21.7	30.5	17.7	22.3	17.7	2.8	28.2
	Kurtosis	511.6	252.5	574.2	1071.2	379.9	634.3	416.0	13.7	845.7
	IQR	1251127	729683	178405	275070	66689	292186	0.01	0.12	5.73

Table 2.8: Summary statistics for selected variables

Beta is the Glasserman & Young (2014) β for the banking sector in Germany. It is calculated as a ratio of Interbank Liabilities / (Total Assets - Equity). Data sources: Monatliche Bilanzstatistik and Millionenevidenzdaten (both from Deutsche Bundesbank), November 2013.

Correlation matrix
(40763 observations)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1 Change of net liabilities to other banks (Φ)	1.00															
2 Change of net long-term liabilities to other banks (Φ_{LT})	0.39	1.00														
3 Change of net short-term liabilities to other banks (Φ_{ST})	0.13	-0.06	1.00													
4 Liquidity need (θ)	0.38	0.18	0.05	1.00												
5 Change of G&Y indicator ($\Delta\Psi$)	0.29	0.37	0.06	0.20	1.00											
6 Credit cooperative dummy	0.02	0.01	0.02	0.01	0.04	1.00										
7 Liquidity need (θ) x credit cooperative dummy	0.33	0.16	0.05	0.85	0.17	-0.03	1.00									
8 Change of G&Y indicator ($\Delta\Psi$) x credit cooperative dummy	0.28	0.32	0.07	0.17	0.86	-0.01	0.20	1.00								
9 Change of other assets (ΔA_o)	0.35	0.19	0.05	-0.11	0.32	0.06	-0.13	0.26	1.00							
10 Change of other liabilties (ΔL_o)	-0.07	-0.04	-0.01	0.13	-0.01	0.05	0.09	-0.01	0.20	1.00						
11 Bank size (A)	-0.01	0.00	-0.01	-0.02	-0.01	-0.58	0.00	0.02	-0.02	-0.05	1.00					
12 Leverage (A/w)	-0.02	0.00	-0.01	-0.04	0.04	-0.25	-0.03	0.04	0.01	0.00	0.32	1.00				
13 Change of equity (Δw)	-0.01	0.00	-0.03	0.04	-0.08	0.03	-0.02	-0.08	0.37	0.33	0.01	-0.04	1.00			
14 Change of intragroup lending (ΔG)	0.00	0.00	-0.01	0.11	0.03	0.01	0.00	0.00	0.04	0.09	-0.01	0.00	0.08	1.00		
15 Centrality in interbank market (C_e)	0.07	0.05	-0.01	-0.03	0.07	0.02	-0.04	0.05	0.22	0.03	-0.02	0.00	0.08	0.02	1.00	
16 Change of creditor/debtor ratio (ΔR)	-0.03	-0.02	0.01	0.04	-0.01	0.00	0.03	-0.01	-0.11	0.01	0.00	0.00	-0.01	0.02	-0.53	1.00

Table 2.9: Correlation matrix main model for effect of credit cooperatives

Correlation matrix

(61430 observations)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1 Change of gross short-term interbank liabilities (Φ'_{ST})	1.00														
2 Change of interbank assets (ΔA_{IB})	0.11	1.00													
3 Liquidity need (θ)	0.07	-0.31	1.00												
4 Change of G&Y indicator ($\Delta\Psi$)	0.41	0.02	0.21	1.00											
5 Credit cooperative dummy	0.05	-0.01	0.01	0.03	1.00										
6 Liquidity need (θ) x credit cooperative dummy	0.05	-0.28	0.89	0.19	-0.02	1.00									
7 Change of G&Y indicator ($\Delta\Psi$) x credit cooperative dummy	0.39	-0.01	0.19	0.88	-0.01	0.22	1.00								
8 Change of other assets (ΔA_O)	0.25	-0.22	-0.10	0.30	0.05	-0.11	0.26	1.00							
9 Change of other liabilties (ΔL_O)	0.15	0.07	0.14	0.00	0.05	0.11	0.01	0.20	1.00						
10 Bank size (A)	0.32	0.07	0.04	-0.08	0.03	0.00	-0.07	0.37	0.31	1.00					
11 Leverage (A/w)	-0.02	0.01	-0.02	-0.01	-0.58	0.00	0.02	-0.01	-0.05	0.01	1.00				
12 Change of equity (Δw)	0.00	0.02	-0.04	0.03	-0.27	-0.03	0.03	0.01	0.00	-0.04	0.37	1.00			
13 Change of intragroup lending (ΔG)	0.03	0.01	0.09	0.02	0.00	0.00	0.00	0.03	0.07	0.07	-0.01	0.00	1.00		
14 Centrality in interbank market (C_e)	0.05	-0.05	-0.02	0.07	0.02	-0.02	0.05	0.21	0.03	0.07	-0.02	0.00	0.02	1.00	
15 Change of creditor/debtor ratio (ΔR)	0.00	0.03	0.05	-0.01	-0.01	0.04	-0.01	-0.10	0.03	-0.01	0.00	0.01	0.02	-0.48	1.00

Table 2.10: Correlation matrix main model for gross short-term interbank liabilities and credit cooperatives

2.7.3 Appendix C: Robustness checks of analysis

This appendix contains three robustness checks of the results obtained in the main section.

The first robustness check is shown in Table 2.11. It presents results of an estimation of the main model but with the diff-in-diff estimator for savings banks rather than for credit cooperatives.

The second check shown in Table 2.12 estimates a similar model to that in the main analysis, but for short-term liabilities to other banks.

Lastly, Table 2.13 shows a robustness check of the second main model estimating the effect of private commercial banks. The robustness check includes a diff-in-diff estimator for non-commercial banks but otherwise estimates the same model.

Coefficients of diff-in-diff model of change in net liabilities to other banks (Φ)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Independent variables							
Liquidity need (θ)	4.43***	5.88***	5.84***	5.87***	5.87***	5.87***	5.94***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Change of G&Y indicator ($\Delta\Psi$)	0.76***	0.36***	0.37***	0.35***	0.35***	0.35***	0.27***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Liquidity need (θ) x	0.74	0.21	0.23	0.45	0.21	0.45	0.74
Savings bank dummy	(0.217)	(0.745)	(0.729)	(0.453)	(0.75)	(0.453)	(0.211)
Change of G&Y indicator ($\Delta\Psi$) x	-0.42***	-0.49***	-0.48***	-0.47***	-0.47***	-0.47***	-0.49***
Savings bank dummy	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Control variables							
Change of other assets (ΔA_o)		1.88***	1.89***	1.9***	1.9***	1.9***	2.17***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Change of other liabilities (ΔL_o)		-0.83***	-0.82***	-0.82***	-0.83***	-0.82***	-0.7***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bank size (A)			-0.1***	-0.1***	-0.1***	-0.1***	-0.04***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage (A/w)			-0.06**	-0.06**	-0.06**	-0.06**	-0.14***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Change of equity (Δw)							-1.35***
							(0.000)
Change of intragroup lending				0.0***		0.0***	0.0***
(ΔG)				(0.000)		(0.000)	(0.000)
Centrality in interbank market				-0.04	0.0	-0.01	-0.01
(C_e)				(0.118)	(0.833)	(0.542)	(0.662)
Change of creditor/debtor ratio						-0.03	-0.02
(ΔR)						(0.108)	(0.326)
Time FE (not shown)							
Time x Savings bank dummy FE (not shown)							
Bank FE (not shown)							
Observations	62590	62590	62590	61360	61460	61460	61460
Number of groups	1632	1632	1632	1617	1617	1617	1617
Error Standard Deviation	0.49	0.46	0.46	0.46	0.46	0.46	0.45
Fixed-effect variance	0.01	0.02	0.08	0.07	0.07	0.07	0.04
Goodness of Fit (adj.)	0.17	0.28	0.28	0.28	0.28	0.28	0.29
F-Statistic (all coeff=0)	53.14	52.93	52.25	50.01	51.05	49.9	48.6

Legend: coefficient/(p-value); * $p < 0.05$,** $p < 0.01$, *** $p < 0.001$

Table 2.11: Control model for effect of savings banks

The regression table shows coefficients and p-values for several diff-in-diff models estimated for all savings banks and credit cooperatives. They regress net liabilities to other banks on two independent variables and some bank-level control variables. The models include interaction effects for savings banks and the explanatory variables in order to analyse whether savings banks show different effects to credit cooperatives. Where appropriate, variables are log-differences and a robust non-parametric estimator is used to calculate standard errors. Change in net liabilities to other banks is interperiod change of net interbank borrowing. Liquidity need is the difference of interperiod changes in loans and interperiod changes in deposits. The G&Y indicator gives an indication of the importance of a bank to the financial system. Control variables account for bank size and leverage, its position in the interbank market, and changes to the balance sheet that would mechanically change net liabilities to other banks. All models control for bank fixed effects, time fixed effects, and time-dummy interaction effects from the diff-in-diff model. Data sources: Monatliche Bilanzstatistik and Millionenevidenzdaten (both from Deutsche Bundesbank).

Coefficients of diff-in-diff model of change in net short-term liabilities to other banks (Φ_{ST})							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Independent variables							
Liquidity need (θ)	0.41	0.55*	0.54*	0.6*	0.52*	0.6*	0.72**
	(0.099)	(0.026)	(0.029)	(0.01)	(0.036)	(0.01)	(0.002)
Change of G&Y indicator ($\Delta\Psi$)	0.0	-0.07	-0.06	-0.06	-0.06	-0.06	-0.1
	(0.967)	(0.164)	(0.191)	(0.231)	(0.215)	(0.207)	(0.051)
Liquidity need (θ) x	0.29	0.36	0.36	0.31	0.39	0.31	0.21
Credit cooperative dummy	(0.273)	(0.166)	(0.172)	(0.218)	(0.144)	(0.222)	(0.398)
Change of G&Y indicator ($\Delta\Psi$) x	0.26***	0.27***	0.27***	0.25***	0.25***	0.25***	0.26***
Credit cooperative dummy	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Control variables							
Change of other assets (ΔA_o)		0.27***	0.27***	0.3***	0.3***	0.3***	0.39***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Change of other liabilities (ΔL_o)		-0.12***	-0.12***	-0.12***	-0.12***	-0.12***	-0.08**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.007)
Bank size (A)			-0.03*	-0.03	-0.03*	-0.03*	-0.01
			(0.042)	(0.053)	(0.033)	(0.036)	(0.339)
Leverage (A/w)			-0.02	-0.02	-0.02	-0.02	-0.04
			(0.47)	(0.54)	(0.577)	(0.588)	(0.118)
Change of equity (Δw)							-0.42***
							(0.000)
Change of intragroup lending				0.0**		0.0**	0.0**
(ΔG)				(0.006)		(0.005)	(0.008)
Centrality in interbank market				-0.11***	-0.08***	-0.08**	-0.08**
(C_e)				(0.000)	(0.000)	(0.001)	(0.002)
Change of creditor/debtor ratio						0.0	0.01
(ΔR)						(0.881)	(0.691)
Time FE (not shown)							
Time x Cooperative bank dummy FE (not shown)							
Bank FE (not shown)							
Observations	54706	54706	54706	53778	53858	53858	53858
Number of groups	1616	1616	1616	1600	1600	1600	1600
Error Standard Deviation	0.49	0.49	0.49	0.49	0.49	0.49	0.49
Fixed-effect variance	0.05	0.05	0.05	0.04	0.04	0.04	0.04
Goodness of Fit (adj.)	0.02	0.02	0.02	0.02	0.02	0.02	0.03
F-Statistic (all coeff=0)	11.24	11.4	11.36	11.09	11.22	11.11	11.49

Legend: coefficient/(p-value); * $p < 0.05$,** $p < 0.01$, *** $p < 0.001$

Table 2.12: Control model for short-term interbank liabilities and credit cooperatives

The regression table shows coefficients and p-values for several diff-in-diff models estimated for all savings banks and credit cooperatives. They regress net short-term liabilities to other banks on two independent variables and some bank-level control variables. The models include interaction effects for credit cooperatives and the explanatory variables in order to analyse whether credit cooperatives show different effects to savings banks. Where appropriate, variables are log-differences and a robust non-parametric estimator is used to calculate standard errors. Change in net liabilities to other banks is interperiod change of net interbank borrowing. Liquidity need is the difference of interperiod changes in loans and interperiod changes in deposits. The G&Y indicator gives an indication of the importance of a bank to the financial system. Control variables account for bank size and leverage, its position in the interbank market, and changes to the balance sheet that would mechanically change net liabilities to other banks. All models control for bank fixed effects, time fixed effects, and time-dummy interaction effects from the diff-in-diff model. Data sources: Monatliche Bilanzstatistik and Millionenevidenzdaten (both from Deutsche Bundesbank).

Coefficients of diff-in-diff model of change in net liabilities to other banks (Φ)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Independent variables							
Liquidity need (θ)	0.13	0.22**	0.22**	0.2*	0.2*	0.2*	0.21*
	(0.076)	(0.006)	(0.007)	(0.044)	(0.045)	(0.043)	(0.037)
Change of G&Y indicator ($\Delta\Psi$)	0.91***	0.87***	0.88***	0.81***	0.83***	0.83***	0.82***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Liquidity need (θ) x	4.47***	4.99***	4.96***	5.13***	5.11***	5.11***	5.13***
Non-commercial bank dummy	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Change of G&Y indicator ($\Delta\Psi$) x	-0.25**	-0.39***	-0.38***	-0.36**	-0.38**	-0.38**	-0.39**
Non-commercial bank dummy	(0.001)	(0.000)	(0.000)	(0.005)	(0.001)	(0.001)	(0.001)
Control variables							
Change of other assets (ΔA_o)		0.8***	0.8***	0.98***	0.98***	0.98***	1.02***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Change of other liabilities (ΔL_o)		-0.5***	-0.49***	-0.57***	-0.58***	-0.58***	-0.55***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bank size (A)			-0.04**	-0.06***	-0.06***	-0.06***	-0.04**
			(0.008)	(0.000)	(0.000)	(0.000)	(0.001)
Leverage (A/w)			-0.11***	-0.1***	-0.09***	-0.09***	-0.12***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Change of equity (Δw)							-0.26
							(0.133)
Change of intragroup lending				0.0		0.0	0.0
(ΔG)				(0.152)		(0.148)	(0.17)
Centrality in interbank market				-0.02	0.04	0.03	0.04
(C_e)				(0.63)	(0.105)	(0.301)	(0.191)
Change of creditor/debtor ratio						-0.01	-0.01
(ΔR)						(0.406)	(0.436)
Time FE (not shown)							
Time x Cooperative bank dummy FE (not shown)							
Bank FE (not shown)							
Observations	67451	67449	67449	64612	64885	64885	64885
Number of groups	1885	1885	1885	1749	1753	1753	1753
Error Standard Deviation	0.51	0.49	0.49	0.48	0.48	0.48	0.48
Fixed-effect variance	0.08	0.1	0.12	0.09	0.09	0.09	0.08
Goodness of Fit (adj.)	0.26	0.3	0.3	0.26	0.27	0.27	0.27
F-Statistic (all coeff=0)	53.0	55.56	56.12	54.25	56.24	55.17	53.76

Legend: coefficient/(p-value); * $p < 0.05$,** $p < 0.01$, *** $p < 0.001$

Table 2.13: Control model for effect of non-commercial banks

The regression table shows coefficients and p-values for several diff-in-diff models estimated for all universal credit banks in Germany. They regress net liabilities to other banks on two independent variables and some bank-level control variables. The models include interaction effects for non-commercial banks and the explanatory variables in order to analyse whether non-commercial banks show different effects to other universal banks. Where appropriate, variables are log-differences and a robust non-parametric estimator is used to calculate standard errors. Change in net liabilities to other banks is interperiod change of net interbank borrowing. Liquidity need is the difference of interperiod changes in loans and interperiod changes in deposits. The G&Y indicator gives an indication of the importance of a bank to the financial system. Control variables account for bank size and leverage, its position in the interbank market, and changes to the balance sheet that would mechanically change net liabilities to other banks. All models control for bank fixed effects, time fixed effects, and time-dummy interaction effects from the diff-in-diff model. Data sources: Monatliche Bilanzstatistik and Millionenevidenzdaten (both from Deutsche Bundesbank).

Chapter 3

The Emergence of Interbank Exposures

Interbank markets are conventionally considered to serve financial institutions to balance out regional or temporal liquidity shocks (Allen and Gale, 2000; Bhattacharya and Fulghieri, 1994; Freixas, Parigi and Rochet, 2000). Such models consider interbank credit lines that allow banks to draw on liquidity when depositors demand to withdraw more liquid funds than a bank holds in reserves. Besides interbank loans, banks are also exposed to each other through other channels such as derivative contracts or credit default swaps. We use the terms interbank lending and interbank exposures interchangeably for the purpose of this model with interbank loans posing the lower bound of interbank exposures. We use the term bank and take it to include any type of financial institution that engages in bank-like activities. We argue below that it is not necessary for the model to distinguish different types of banks, because the set-up is such that parameters can be type-specific. Similarly, parameters describing regulatory uncertainty can also change over time and differ between countries.

We have shown in Chapter 2 that the behaviour of banks in the interbank market is dependent on the governance structure of a bank. While the empirical results show that managing interbank liabilities is the main function of the interbank markets for a majority of banks, especially for private commercial banks additional drivers must be taken into account. For private banks it was shown that interbank market activities correlate with a proxy indicator for systemic importance. This banking group makes up for more than half of the banking sector (in Germany) and includes many of the largest banking institutions in a country. In this chapter we are studying a model of optimal bank behaviour aimed at improving our understanding of the effect of uncertain bailout probabilities on the emergence of interbank co-exposures.

In our model we set aside liquidity co-insurance and focus on an alternative rationale for the emergence of interbank markets. We study the behaviour of banks in a system in which their importance to the system as a whole influences market expectations with regards to default probabilities. We show that the presence of a regulator, or some sort of uncertain liability guarantees, is sufficient for interbank lending to emerge as an equilibrium outcome. The model shows that any such equilibrium is characterised by banks of different sizes and asymmetric behaviour. Some banks in the system are active as lenders in the interbank market only. These banks will be small in terms of total balance sheet size when comparing them to borrowers in the interbank market. Borrowers invest both their own funds as well as the borrowed funds in a productive technology.

Preceding the formulation of the model we describe the structure of bank balance sheets in different countries. We find variation that is large within countries, but also that the distribution of bank balance sheet compositions differs between countries. We thus specify the bailout probability of a bank in terms of bank-specific factors and introduce a flexible function that considers uncertainty regarding bailout decisions. The function is flexible enough to be parametrised to reflect inter-country differences. We characterise the equilibrium interbank rate, which includes parameters for bailout uncertainty and a threshold for the systemic importance of a bank.

We show that irrespective of liquidity needs, interbank markets (or more generally interbank exposures) can be a consequence of competitive behaviour of banks if the importance of a bank to the financial system has any bearing on the probability that its liabilities will be guaranteed in a situation of distress. Our model allows us to determine under what conditions interbank markets are bound to exist. In particular we show how the probability of default of a productive technology and its expected payoff interact with the costs of running a bank, and how the likelihood of bank bailouts influence the probability of whether interbank markets come into being. We show that under some parameter configurations the existence of potential bank bailouts will induce banks to enter lending and borrowing relationships. This result adds to the list of critiques of 'Too-Big-To-Fail' policies (Rochet and Tirole, 1996; Shapiro and Skeie, 2015). Any such guarantees encourage a higher degree of interconnectedness between financial institutions, i.e. exacerbate the cause of the effect they seek to alleviate. Of course, once we allow for the fact that both mechanisms, liquidity management and strategic behaviour, operate in conjunction as drivers of financial co-exposures the question may arise what determines which mechanism is dominant and when. We leave the empirical answer to this question to future research but in Chapter 4 introduce a model of network formation that considers both effects together.

We have shown in Chapter 2 that the governance structure of banks matters for incentives to enter interdependencies. Throughout the model discussion in this chapter we do not distinguish different types of banks. While the results are most relevant to private commercial banks who do not enjoy any explicit public guarantees (cf. Chapter 2), the specific uncertainties and probabilities as captured by the bailout function can be parameterised to each bank type. So at least in principle our discussion and results apply equally to all bank types. To stick with common nomenclature, we refer to all financial institutions simply as banks, regardless of whether they are commercial banks, regional banks, cooperative banks, hedge funds, or other entities. The overall system of interdependencies we call the interbank market, the interaction between financial institutions interbank lending. Interbank lending hence subsumes a multitude of liability exposures such as interbank loans, repo-contracts, off-balance-sheet transactions, or obligations arising from derivative contracts. When using the term interbank loan, we refer to the total liability exposure that exists between any two financial institutions.

The chapter proceeds as follows. We begin by introducing two empirical observations regarding interbank lending. First, the composition of bank balance sheets is diverse within countries and independent of the size of banks. Second, the distributions of interbank market activity (the proportion of interbank borrowing of the balance sheet of a bank) differ between countries. We proceed to introduce a model of bank behaviour in interbank markets that sets aside liquidity considerations, but allows us to account for those empirical observations. We discuss our results briefly with a view to extensions and the applicability to empirical work.

3.1 International variation of interbank market structures

A high degree of interconnectivity within financial systems is a well documented phenomenon (cf. Chapter 1). We think specifically of interconnectivity in the sense of bilateral liabilities between financial institutions (Eisenberg and Noe, 2001). However, interlinkages exist not only because of direct borrowing or lending relationships, but also because of co-exposure to common asset-classes and through derivative contracts. In their study of cross-border banking flows between 184 countries Minoiu and Reyes (2013) document an increase in cross-border exposures of financial institutions between 1978 and 2010. They further show that connectedness increases before financial crises and decreases afterwards. Minoiu and Reyes point to the fact that their data shows cross-border financial exposures between legally separated entities. This means that bank subsidiaries are treated as individual institutions because they report cross-border exposures to national regulators.[25] Therefore, an increase in connectedness may partially arise from increasing cross-border exposures within financial institutions. Those could be driven by increased international activities of universal banks as well as consolidations within the sector. This interpretation of their results is supported by the fact that the largest volumes of out-exposures, i.e. cross border loans, existed in the UK, US, France, and Japan in 1980 and the UK, France, US, Japan, and Germany in 2007 (cf. Table 3 in Minoiu and Reyes). All of those countries are home to large international banks and banking hubs. Their study is thus a reminder that in order to understand bank behaviour in interbank markets, one needs to keep increased international within-group exposures in mind.

---

[25] The bank supervision of the largest banks in Europe is carried out centrally by the European Central Bank. However, the reporting of cross-border financial flows is still done based on national reporting systems.

While bilateral exposures across national borders are usually not available to researchers or central banks, banks report loans and advances to other banks and deposits from banks on their balance sheet. Those on-balance-sheet exposures pose a lower bound of actual exposures and are thus a conservative estimate assuming that on-balance-sheet exposures and cross-border exposures scale in the same way. On-balance-sheet exposures have the advantage that they are less distorted by reporting artefacts. By analysing the balance sheets of banks, we can thus get a sense of interbank markets. In the following we show a comparison of the β_i of banks as defined by Glasserman and Young (2015). The β_i for a bank, which lies in the interval $(0, 1)$, is defined as

$$\beta_i = \frac{L_i^{IB}}{L_i^{IB} + L_i^{O}}, \tag{3.1}$$

where L_i^{IB} are total interbank liabilities (bank deposits) and L_i^{O} are liabilities to outside of the financial sector such as deposits. Glasserman and Young show that the likelihood of contagion in financial systems from shocks to individual entities depends on the β_is of those entities. Their theorem 1 states that contagion from one institution to a set of banks D is impossible if the following condition holds true:

$$\sum_{j \in D} w_j / w_i > \beta_i(\lambda_i - 1), \tag{3.2}$$

where w_i is the equity (or net worth) of a bank and $\lambda_i = (L_i^{O}/w_i)$ the leverage of liabilities outside of the financial system. Roughly speaking, the higher an entity's β_i, the higher the likelihood that adverse shocks to this entity will spill over to other entities in the system.[26] It is therefore informative to compare β_is both over time

---

[26] In order to fully understand the probability of contagion, we further need to take into account the magnitude of the liabilities of financial institutions. By just analysing β_is we thus are somewhat oversimplifying, but get a sense of market structure and specifically the role of interbank lending.

and for different countries.

Figure 3.1 shows the distribution of β_is in different countries and how they evolve over time.[27] We have previously discussed the risk of exaggerating interbank exposures because of exposures between international subsidiaries. Here we only consider banks that are publicly traded in the respective country, which gets rid of this effect. We therefore have a conservative estimate of β_is. One can immediately deduct that in Japan, for instance, the exposure of the financial system to individual banks is low on average but also includes a fat tail of high β_is. In contrast, averages in Great Britain and Germany are higher, but also more evenly dispersed. The underlying distribution of β_is thus seems to be a defining characteristic of financial systems.

Figure 3.2 compares Great Britain and Germany in some more detail. The magnitude of the β_i of a bank is independent of its total assets. Variation in β_is is thus not merely an artefact of bank size but constitutes a measure that allows researchers to genuinely distinguish the behaviour of banks in interbank markets. It thus also provides an indication of differences between interbank market structures. Therefore, when studying the evolution and structure of interbank markets we need to be mindful to account for factors that i) lead to different distributions of β_is between countries and ii) can explain intracountry differences as well.

The remainder of the chapter develops our model and discusses its implications.

3.2 Model

Following the work of Diamond and Dybvig (1983), and Allen and Gale (2000) we consider an economy with three time periods ($t = 1, 2, 3$) populated by an arbitrary

---

[27] The plots have been generated using data from Bankscope. Some of the applied filters (only such entries with an ISIN number are considered) make periods before 2012 less complete in terms of information.

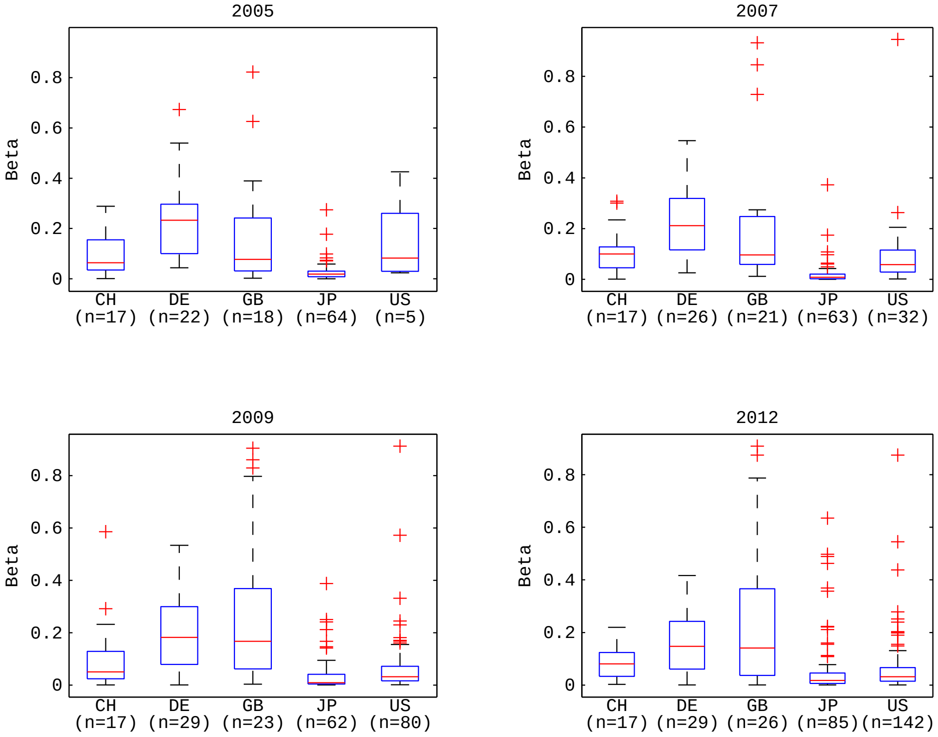


Figure 3.1: Intercountry comparison of bank β_is over time

Beta is calculated as a ratio of Interbank liabilities / (Total assets - Equity). The figure shows a comparison of the distribution of βs of banks in the respective country. Only such banks are considered that have an ISIN number and existed in 2012. While the number of banks is relatively stable in Switzerland, Germany, Great Britain, and Japan, for dates before 2009 Bankscope offers unsatisfactory data for the US. ISIN numbers can change because of mergers or acquisitions. Source: Created by author, data from Bankscope [Retrieved: 17 November 2013].

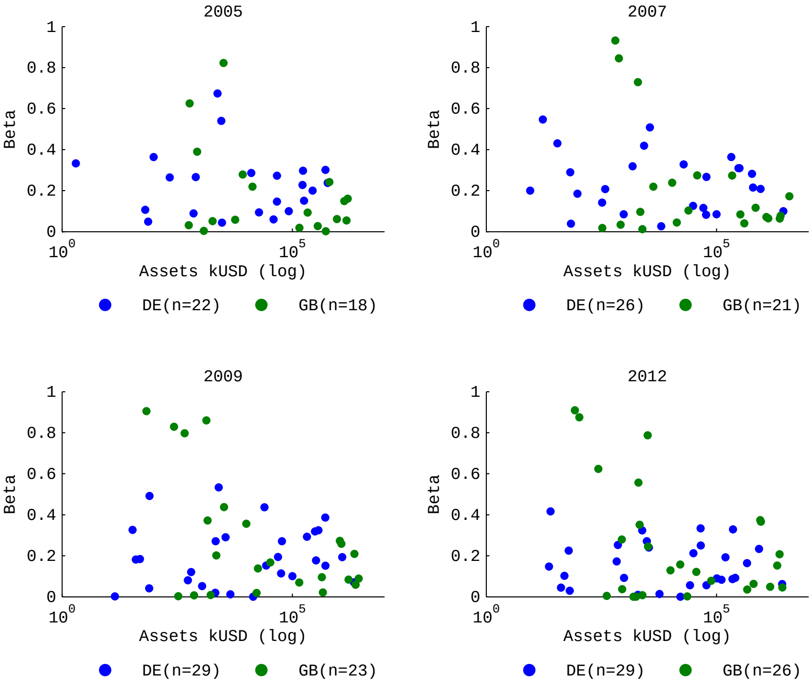


Figure 3.2: Comparison of bank β_is in Germany and the UK

Beta is calculated as a ratio of Interbank liabilities / (Total assets - Equity). The figure shows a scatterplot of assets in log-scale and β for banks in Germany and Great Britain. Only such banks are considered that have an ISIN number and existed in 2012. Source: Created by author, data from Bankscope [Retrieved: 17 November 2013].

but even number of consumers endowed with fixed initial wealth. For the purpose of this model we fix total initial wealth at $\omega = 2$ without loss of generality.[28] Consumers can either store their wealth or invest it in a bank that acts as a cooperative investment vehicle. We assume that consumers are risk-neutral. There are up to two banks in the economy (1 and 2) that exist for one period and act on behalf of their owners. Banks invest aggregated wealth in a productive technology (loans to firms and households) at some operating cost $c(\delta)$ that is a simple monotonically increasing function of balance sheet size with a cost parameter $\delta \geq 0$. The productive technology offers a return of $r^A \geq 1 + \delta$ with some probability $(1 - p)$ and generates a loss of $0 \leq \kappa < 1 + \delta$ with probability p, where $0 \leq p \leq 1$. The productive technology thus generates a return for investors in a bank in excess of costs of running a bank in the non-default case and generates a loss in the default case. Should banks form in the economy, they can engage in interbank lending in period $t = 2$. Given banks have operating costs and can enter lending contracts, it is possible for banks to become insolvent. We model an agent exogenous to the interaction between consumers and banks, which could be the regulator or consortium of other banks, that in the event of insolvency can guarantee the liabilities of a bank. We explore the relationship between the structure of interbank lending and the behaviour of the external agent, which in the following is simply identified as government.

The actions during the time periods of the model are as follows:

1. Consumers make investment decisions ($t = 1$),
2. If banks exist, they make interbank lending and borrowing decisions and invest in productive technology ($t = 2$),

---

[28] It is evident form the following exposition that the total level of wealth in the economy determines the size of banks at $t = 2$ and in that sense is a factor of scale rather than qualitatively influencing results. The assumption of $\omega = 2$ allows us to normalise the initial size of banks to 1 whenever banks (initially) are of the same size, which clarifies the following analysis greatly.

3. Payoffs are realised ($t = 3$), banks are resolved.

Throughout, whenever variables assume different values in different time periods, we indicate the time period through a superscript (t). In the first time period ($t = 1$), consumers allocate their wealth. We assume a linear return to their investments and ignore any spatial or other ex-ante preferences for banks. Therefore, consumers allocate all their wealth to the bank with the highest expected returns or split their wealth evenly between banks if expected returns are equal. If economic agents do not expect a positive return from investing in a collective investment vehicle (bank), no banks form and consumers keep their wealth. There are up to two banks, which in the following we distinguish by subscripts $i = 1, 2$. Depending on the investment decisions of consumers, the deposited wealth constitutes the capital of a bank i at time period $t = 2$ which we denote by $C_i^{(2)}$. We assume that banks act in the interest of their shareholders only and maximise expected wealth, which is the expected value of equity in time period $t = 3$ or $E[C_i^{(3)}]$.

Banks act as cooperative investment vehicles, aggregating the wealth of agents and investing it in a productive technology. Banks can also lend to and borrow from each other. We denote interbank lending of bank i by A_i^{IB} and interbank borrowing as L_i^{IB}. Banks agree on an interbank lending and borrowing rate, where the interest rate on the lending of one bank is the interest rate on the borrowing of another. We have $r_1^L = r_2^B$, and vice versa $r_1^B = r_2^L$. Banks use their capital in excess of interbank loans $A_i = L_i^{IB} + C_i^{(2)} - A_i^{IB}$, to invest in the productive technology. Operating costs $c(L_i^{IB}, C_i^{(2)})$ are payable in period $t = 3$ and for simplicity sake are assumed to be a linear function of balance sheet size $c(L_i^{IB}, C_i^{(2)}) = \delta(L_i^{IB} + C_i^{(2)})$, where $0 \leq \delta \ll r^A$.

Before discussing the strategic behaviour of banks in period $t = 2$, we describe the government bailout function and characterise the expected value of bank equity depending on the state of the world.

3.2.1 Government bail-out function

In the case of insolvency of a bank, governments or another external agent such as banking consortia can decide whether or not to guarantee liabilities of a bank. We denote the event of insolvency of bank i by I_i and the bailout of bank i by B_i. We therefore denote the probability of bailout in the case of insolvency by $P(B_i|I_i)$. Depending on economic circumstance, timing, and legal environment, the probability of such a bailout will depend on a multitude of factors. It has been shown that central banks or regulators can take advantage of the uncertainty of bailout decisions and thus have an incentive to maintain 'creative ambiguity' (Freixas, 1999; Shapiro and Skeie, 2015). If strict free-market policies are followed, the likelihood of bailout would be zero, while in times of an acute crisis marked by systemic instability and interventionist economic policies, the likelihood of a bailout will be higher. We assume that this decision depends on a publicly observable signal that characterises the importance of a bank. We denote this signal by $\beta_i \in [0,1]$. It is an open area of research what exactly shapes the market expectation regarding bailout probabilities. Recent research into the systemic importance of banks involves a consideration of their position in a network of interbank liabilities (Gai, 2013; Hüser, 2015). We use the measure based on Glasserman and Young (2015) introduced above, which characterises the likelihood that a bank embedded in a network of payment obligations can lead to defaults of other banks, and under the simplified balance sheet set-up in our model becomes:

$$\beta_i = \frac{L_i^{IB}}{L_i^{IB} + C_i^{(2)}}. \tag{3.3}$$

We assume that β_i is a publicly observable indicator that is used to determine the bailout probability of a bank $F_{\mathbf{B}}(\beta_i)$. We abstract from the intricacies of the bailout decision by using a probability function of the form $F_{\mathbf{B}}(\beta_i) : \mathbb{R} \rightarrow [0,1]$.[29] Any type of continuous function including step-sized functions and smooth functions are candidates. Any such function needs to allow for the flexibility to capture different legal and political environments. We use the following function defined for $\beta_i \in [0,1]$:[30]

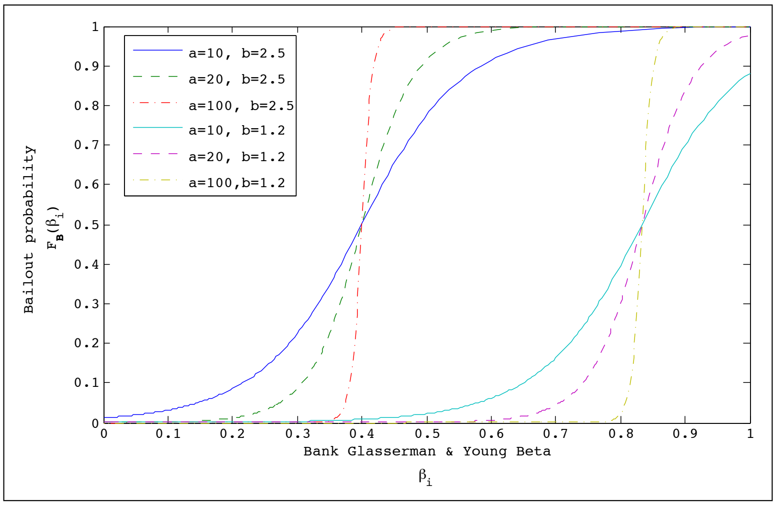


Figure 3.3: Bailout probability function

The figure shows two families of the function modelling the probability of bailout of a bank. A bank's publicly observable β_i *determines the likelihood of a bank bailout. The probability is determined by two parameters,* $a > 0$ *and* $b > 0$*.* a *captures the uncertainty regarding a bailout and* b *captures the threshold for a bailout to occur. The function* $F_{\mathbf{B}}(\beta_i) = \frac{2}{\pi} tan^{-1}\left[e^{(a\beta_i - \frac{a}{b})}\right]$ *represents the bailout probability and the graph shows the effect of variations in the function parameters* a *and* b*.*

$$F_{\mathbf{B}}(\beta_i) = \frac{2}{\pi} tan^{-1}\left[e^{(a\beta_i - \frac{a}{b})}\right]. \tag{3.4}$$

Figure 3.3 shows plots of some parameter values for $a > 0$ and $b > 0$. The parameters characterise the policy environment. a can be thought of as an uncertainty indicator.

---

[29] Because of our choice of β_i, we have $F_{\mathbf{B}}(\beta_i) : [0,1] \rightarrow [0,1]$ even though this is by no means necessary.

[30] The equation is a rescaled version of a local solution to the sine-Gordon equation (e.g. Rajaraman, 1987). It offers the desirable qualities of a flexible function allowing for modelling uncertainty while being continuously differentiable and analytically tractable. The incomplete Beta function of the form $B(\beta_i; a, b) = \int_0^{\beta_i} u^{a-1}(1-u)^{b-1}du$ would also be such a function, but it does not offer closed form analytical solutions.

The smaller a, the more uncertainty there is around the bailout of a bank. For very large a, the function becomes a step function. So, depending on the publicly observable signal, a bank is either bailed out or not. b can be thought of as a bailout threshold. The smaller b, the higher the threshold for a bank to be bailed out. So, if $b = a \to \infty$ banks would always be bailed out. Similarly, if $b \to 0$, $a \to \infty$ banks would never be bailed out.

3.2.2 Payoff to consumers and equity value of banks

Let $P(I_i \backslash B_i)$ be the probability of a bank to default. This is the probability of a bank being insolvent (I_i) and not bailed out by the government ($\backslash B_i$). Let $(I_i|r)$ denote the event that bank i becomes insolvent given the return realisation r of the productive technology. A bank is insolvent if the equity in $t = 3$ becomes smaller than zero, or the returns from the technology and interbank lending are smaller than liabilities to other banks and costs: $rA_i + r_i^L A_i^{IB} < r_i^B L_i^{IB} + c(L_i^{IB}, C_i^{(2)})$. We denote the probability of insolvency by $\Psi_i(r) = P(I_i|r)$:

$$\Psi_i(r) = \begin{cases} 1 & \text{if} \quad \frac{\delta(L_i^{IB}+C_i^{(2)})+r_i^B L_i^{IB}-r_i^L A_i^{IB}}{r(C_i^{(2)}+L_i^{IB}-A_i^{IB})} > 1 \\ 0 & \text{otherwise} \end{cases} \tag{3.5}$$

and the probability of default as:

$$\Phi_i = P(I_i|r)\left(1 - P(B_i|I_i)\right) \tag{3.6}$$

or

$$\Phi_i = \Psi_i(\kappa)\left(1 - F_{\mathbf{B}}(\beta_i)\right). \tag{3.7}$$

We assume that the payoffs of r^A, κ, and operating costs δ are common knowledge.

For banks to exist they must have a positive expected equity value in period $t = 3$. Thus, no interbank contracts are permissible that would lead to a default of a bank in the case of positive returns to the technology $r = r^A$ and we therefore know that $\Psi_i(r^A) = 0$ for both $i = 1$ and $i = 2$.[31] As a consequence, the following condition needs to hold in our model

$$\frac{\delta(L_i^{IB} + C_i^{(2)}) + r_i^B L_i^{IB} - r_i^L A_i^{IB}}{r^A(C_i^{(2)} + L_i^{IB} - A_i^{IB})} \leq 1. \tag{3.8}$$

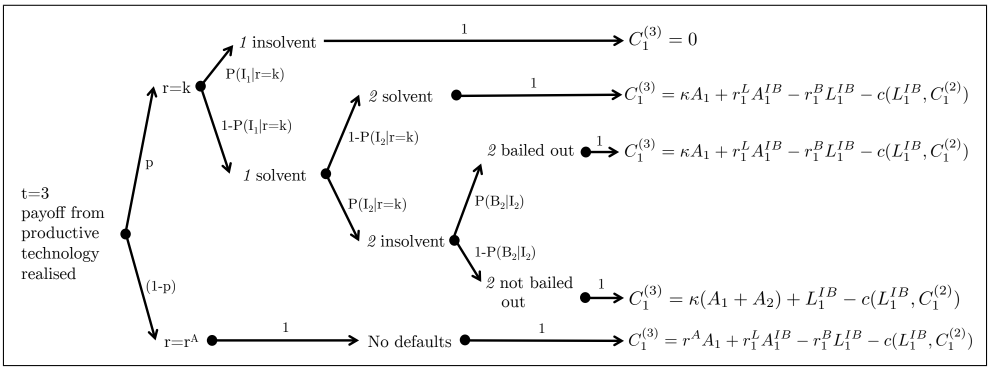


Figure 3.4: Expected value of equity stake

The chart shows the equity value (net worth) of bank $i = 1$ at $t = 3$ under all possible states of the world and the respective probabilities of those states of the world to occur. This schematic representation allows for deriving the expected worth of a bank's equity in $t = 3$.

We can derive the equity value of bank $i = 1$ at $t = 3$ in all states of the world and using the respective probabilities as depicted in Figure 3.4 determine the expected equity value $E[C_1^{(3)}]$, which is the basis of our further analysis. The case for bank $i = 2$ is symmetric. It is straightforward to derive the equity value in the case of high returns $r = r^A$ or when the technology returns κ, but no bank becomes insolvent. When a bank becomes insolvent in a given period, we assume that its equity value

---

[31] This premise ensures that there are no direct government subsidies of inefficient technologies. It could be argued that it is optimal for banks to finance technologies with negative returns if they expect their liabilities to be guaranteed. This is not the purpose of the model and is thus precluded.

becomes zero. Bailouts can assume two forms, equity injections or asset buyouts (Bhattacharya and Nyborg, 2013). In both cases the objective is to protect debtors rather than equity holders. Therefore, we assume the prices in either asset buyouts or capital injections are such that the equity value of a bank would become zero. The demarcation between a bailout and non-bailout is that in the former case the liabilities of a bank will be fulfilled but not in the latter. This is in line with empirical observations. The share price of banks bailed out during the 2007-2009 financial crisis collapsed to a level close to zero with equity holders losing more than 95 percent of their wealth.[32] In a modelling context it is therefore prudent to assume an equity value of zero rather than a residual value which arguably would exist in practice.

If bank 1 becomes insolvent, the worth of its equity share will therefore be zero. If bank 2 becomes insolvent, the equity value of bank 1 depends on whether bank 2 is bailed out or not. In the case of no bail-out we can determine the equity value by using unique clearing vectors of the payment system (Eisenberg and Noe, 2001) and find the resulting net payments. Any clearing vector needs to satisfy both limited liability and absolute priority. Therefore, if a bank defaults its equity value becomes zero. Thus a bank either satisfies all of its liabilities or pays out all assets to creditors. The different cases are shown in Figure 3.4.

Banks manage interbank lending and borrowing. Due to the balance sheet identity it follows that $A_i = C_i^{(2)} + L_i^{IB} - A_i^{IB}$. The expected payoff function of bank 1 (after

---

[32] The share price of Royal bank of Scotland, which was bailed out in the aftermath of the 2008/2009 financial crisis, stood at over 8,000 GBP in January 2008 and fell to 220 GBP within a year.

some algebra) thus becomes:

$$\begin{gathered}E[C_1^{(3)}] = (1-p)\left(r^A C_1^{(2)} + L_1^{IB}(r^A - r_1^B) + A_1^{IB}(r_1^L - r^A)\right) + \\ p(1-\Psi_1(\kappa))\Big[(1-\Phi_2)(\kappa C_1^{(2)} + L_1^{IB}(\kappa - r_1^B) + \\ A_1^{IB}(r_1^L - \kappa)) + \Phi_2(C_1^{(2)}\kappa + (1+\kappa)L_1^{IB} + (A_2 - A_1^{IB})\kappa)\Big] - \delta(L_1^{IB} + C_1^{(2)})(1 - p\Psi_1(\kappa)),\end{gathered} \tag{3.9}$$

which is the payoff function that forms the basis of all further analysis.

3.2.3 Market clearing and equilibrium identification

We can conceive of three types of equilibria in our economy. The first is an economy in which no banks exist because the expected wealth of banks at dissolution at $t = 3$ ($E[C_i^{(3)}]$) does not offer a a positive return to consumers in the economy. For consumers to form cooperative banks the following condition needs to hold (*participation constraint*):

$$E[C_i^{(3)}] \geq C_i^{(2)}. \tag{3.10}$$

The second equilibrium is one in which banks exist but no interbank lending. The third equilibrium is one in which banks exist and form interbank links.

It follows from Eq. 3.8, which characterises the permissibility of interbank contracts, that interbank borrowing must be such that (*borrowing constraint*):

$$0 \leq L_i^{IB} \leq \frac{r^A}{\delta} - 1. \tag{3.11}$$

Assuming that there are linear costs to running a bank and no scale effects, consumers in $t = 0$ are indifferent between forming one or two banks. As consumers have no natural preference for any of the two banks, for banks to exist they need to have ex-ante the same expected equity value. Therefore, consumers randomly allocate their wealth to banks if the above condition is fulfilled. Thus the initial wealth of $\omega = 2$ is split evenly so that

$$C_1^{(2)} = C_2^{(2)} = 1. \tag{3.12}$$

Banks maximise their expected return in $t = 3$ by entering interbank lending and borrowing contracts. The interbank lending market is cleared using the interbank lending rate r_i^L and interbank borrowing rate r_i^B. We use the Nash Bargaining solution (Nash, 1950) to determine interbank rates. Because the outside option of banks are the same due to symmetry, the interbank lending and borrowing rates must be such that the expected equity value of the two banks are the same at $t = 3$:

$$E[C_1^{(3)}] = E[C_2^{(3)}]. \tag{3.13}$$

3.2.4 Symmetric equilibria

We initially consider symmetric equilibria, which can be solved fairly generally. In any symmetric equilibrium we have $A_i^{IB} = L_i^{IB}$ and hence $r_i^B = r_i^L$. Therefore, the probability $\Psi_i(\kappa)$ becomes

$$\Psi_i(\kappa) = \begin{cases} 1 & \text{if} \quad L_i^{IB} > \frac{\kappa}{\delta} - 1 \\ 0 & \text{otherwise} \end{cases} \tag{3.14}$$

and the payoff function becomes

$$E[C_i^{(3)}] = (1-p)r^A + p(1-\Psi_i(\kappa))(\kappa(1+\Phi_i) + \Phi_i L_i^{IB}) - (1-p\Psi_i(\kappa))\delta(1+L_i^{IB}). \tag{3.15}$$

Optimal level of interbank lending with bank-independent guarantees

There are two scenarios in which the bailout probability of a bank is independent of any specific characteristics of a bank. The one is the absence of guarantees, in which case the probability $F_B(\beta_i)$ is 0 for all β_i and therefore the probability of default is the same as the probability of insolvency $\Phi_i = \Psi_i(\kappa) \in \{0, 1\}$. The payoff function becomes

$$E[C_i^{(3)}] = (1-p)r^A + p\,(1-\Psi_i(\kappa))\left((1+\Psi_i(\kappa))\kappa + \Psi_i(\kappa)L_i^{IB}\right) - (1-p\Psi_i(\kappa))\delta(1+L_i^{IB}). \tag{3.16}$$

The second case is a form of an absolute guarantee of bank liabilities, in which liabilities are always guaranteed, independent of the level of interbank exposures. In this case $F_B(\beta_i) = 1$ for all β_i and therefore banks cannot default, or $\Phi_i = 0$ for all β_i . In both cases the marginal benefit from increasing interbank liabilities is the following:

$$\frac{\partial E[C_i^{(3)}]}{\partial L_i^{IB}} = \begin{cases} -(1-p)\delta & \text{if} \quad L_i^{IB} > \frac{\kappa}{\delta} - 1 \\ -\delta & \text{otherwise} \end{cases}. \tag{3.17}$$

It is easy to see that the marginal effect of increasing interbank exposures is always negative. Therefore, it is never optimal for banks to engage in interbank lending.

Optimal level of interbank lending with non-trivial bailout probabilities

In a world of symmetric actions it must also be the case that whenever bank 2 is insolvent and may be bailed out that bank 1 also is insolvent and therefore its equity value is zero. This intuitive consequence follows immediately from Eq. 3.15 which becomes:

$$E[C_i^{(3)}] = \begin{cases} (1-p)r^A - (1-p)\delta(L_i^{IB}+1) & \text{if} \quad L_i^{IB} > \frac{\kappa}{\delta} - 1 \\ (1-p)r^A + p\kappa - \delta(L_i^{IB}+1) & \text{otherwise} \end{cases} \tag{3.18}$$

and hence

$$\frac{\partial E[C_i^{(3)}]}{\partial L_i^{IB}} = \begin{cases} -(1-p)\delta & \text{if} \quad L_i^{IB} > \frac{\kappa}{\delta} - 1 \\ -\delta & \text{otherwise} \end{cases} . \tag{3.19}$$

Given that $0 \leq p \leq 1$ it is never optimal for banks to engage in interbank lending. It is striking that symmetric actions have the same consequence on the incentives for banks to engage in interbank lending than does the absence of government guarantees altogether.

Benchmark equilibrium

For an equilibrium to produce banks, due to the consumer participation constraint (cf. Eq. 3.10) we need $(1-p)(r^A-\kappa) \geq 1$ when $\kappa < \delta$ and $(1-p)r^A+p\kappa-\delta \geq 1$ when $\kappa \geq \delta$. We therefore obtain the benchmark result. Whenever the actions of banks are either symmetric or bank liabilities are always guaranteed (or never guaranteed) it is never optimal for banks to engage in interbank lending.[33]

Proposition 3.2.1. *As long as interbank lending or borrowing are symmetric, or the bailout policy is absolute and independent of bank characteristics so that* $F_B(\beta_i) = 0 \ \forall \ \beta_i$ *or* $F_B(\beta_i) = 1 \ \forall \ \beta_i$*, it is never optimal for banks to engage in interbank lending. The equilibrium that arises depends on the relationship between returns of the productive technology in the default case* κ *and the costs of running a bank* δ*.*

a) If the lower return from the technology is smaller than the cost of running a

---

[33] It must be noted that we ignore any sort of the temporal or regional liquidity shocks banks may face because of fluctuating deposits as are commonly found in models of banking. This proposition therefore does not preclude other reasons for interbank lending to emerge.

bank ($\kappa < \delta$):

- *No banks exist in the economy if* $(1-p)(r^A - \kappa) < 1$.
- *Otherwise banks exist but do not engage in interbank lending* ($L_i^{IB} = 0$).

b) If the return from the technology is larger or equal to the costs of running a bank ($\kappa \geq \delta$):

- *No banks exist in the economy if* $(1-p)r^A + p\kappa - \delta < 1$.
- *Otherwise banks exist but do not engage in interbank lending* ($L_i^{IB} = 0$).

Provided parameters are such that banks will exist in equilibrium, their payoff in the benchmark case will be as follows, marked by the subscript B.

$$E[C^{(3)}]_B = \begin{cases} (1-p)(r^A - \delta) & \text{if} \quad \kappa < \delta \\ (1-p)r^A + p\kappa - \delta & \text{if} \quad \kappa \geq \delta \end{cases} . \tag{3.20}$$

3.2.5 Asymmetric equilibrium

We now turn to the case where one bank becomes a borrower in the interbank market and the other bank becomes a lender. We constrain the action set of banks so that a bank can either lend all of its initial wealth to the other bank or invest in the productive technology. We already know that in any symmetric case it is suboptimal for banks to engage in interbank lending. We are therefore left with the case in which one bank lends all of its assets to the other bank which invests it in the productive technology. After showing the asymmetric payoff functions, we use the consequence of symmetric outside options of banks in $t = 2$ to derive the equilibrium interbank rate r^{L^*}. We then determine the conditions for an equilibrium with positive levels of interbank lending.

Let bank 1 be the lender and bank 2 be the borrower. Given our assumption that $C_1^{(2)} = C_2^{(2)} = 1$, we thus have $A_1^{IB} = L_2^{IB} = 1$, $A_1 = 0$, and $A_2 = 2$. It follows that the payoff functions of both banks are now asynchronous. We have:

$$E[C_1^{(3)}] = (1-p)r^L + p(1-\Psi_1(\kappa))\left[(1-\Phi_2)r^L + \Phi_2 2\kappa\right] - \delta\left(1 - p\Psi_1(\kappa)\right) \tag{3.21}$$

and

$$E[C_2^{(3)}] = (1-p)(2r^A - r^L) + p(1-\Psi_2)\left[(1-\Psi_1)(2\kappa - r^L) + \Psi_1(1+2\kappa)\right] - 2\delta(1-p\Psi_2). \tag{3.22}$$

Equilibrium interbank rate

It follows from $E[C_1^{(3)}] = E[C_2^{(3)}]$ that the equilibrium interbank lending rate is

$$r^{L^*} = \frac{(1-p)2r^A + p(2\kappa(1+\Phi_2(\Psi_1 - 1) - \Psi_2)) + \Phi_1(\Psi_2 - 1) - \delta(1 + p(\Psi_1 - 2\Psi_2))}{2 + p(\Phi_2(\Psi_1 - 1) - \Psi_1 + \Phi_1(\Psi_2 - 1) - \Psi_2)}. \tag{3.23}$$

Firstly, we can use the interbank rate to check whether this level of interbank lending is permissible. We do so by examining the contract permissibility constraint. If the technology returns r^A, banks cannot become insolvent and thus $\Psi_1 = \Psi_2 = 0$. Given bank 1 faces costs of δ and an income of r^L, we must have $r^L \geq \delta$. We find that the following needs to hold for the contract permissibility constraint to be met:

$$\delta \leq \frac{2}{3}(1-p)r^A + p\kappa. \tag{3.24}$$

We now determine the probabilities of default and insolvency more generally in order to solve for the equilibrium interbank rate. Given that bank 2 is directly affected by any loss from the productive technology we start with the probability of insolvency of bank 2. It follows from Eq. 3.5 that

$$\Psi_2(\kappa) = \begin{cases} 1 & \text{if} \quad \delta + \frac{1}{2}r^L > \kappa \\ 0 & \text{otherwise} \end{cases} \tag{3.25}$$

and consequently

$$\Phi_2 = \begin{cases} 1 - \frac{2}{\pi} tan^{-1}\left[e^{\frac{a}{2} - \frac{a}{b}}\right] & \text{if} \quad \delta + \frac{1}{2}r^L > \kappa \\ 0 & \text{otherwise} \end{cases}. \tag{3.26}$$

Given that the interest r^L on the interbank loan is the only income for bank 1, the probability of insolvency of bank 1 is the same as the probability of default of bank 2:

$$\Psi_1(\kappa) = \Phi_2. \tag{3.27}$$

Because bank 1 has no interbank liabilities, we further know that $\beta_1 = 0$, so we obtain as its probability of default:

$$\Phi_1 = \begin{cases} 1 - \frac{2}{\pi} tan^{-1}\left[e^{-\frac{a}{b}}\right] & \text{if} \quad \delta + \frac{1}{2}r^L > \kappa \\ 0 & \text{otherwise} \end{cases}. \tag{3.28}$$

Therefore, because of the consumer participation constraint, we know that $r^L \geq 1$. The upper bound of values for κ for which bank 2 becomes insolvent is thus $\bar{\kappa} = \frac{1}{2} + \delta$. We study the case for which κ is smaller than this upper bound because otherwise bank defaults would not be possible. The model invokes the tradeoff between running a bank at a cost and the potential rewards from investing in a productive technology. It further ensures a strategic dimension of bank behaviour in which banks can engage in interbank lending, which affects the chance that they are bailed out by a third party. Introducing costs into the model is further supposed to limit the extent to which interbank lending is permissible. κ therefore represents the default case of a technology. The assumption that it returns no more than half of the initial investment does not seem restrictive.

We can thus write the equilibrium interest rate r^{L^*} as:

$$r^{L^*} = \frac{(1-p)2r^A + p(2\kappa(\Phi_2(\Phi_2 - 1))) - \delta(1 + p(\Phi_2 - 2))}{2 + p(\Phi_2(\Phi_2 - 2) - 1)}, \tag{3.29}$$

which is equivalent to:

$$r^{L^*} = \frac{(1-p)2r^A + pF_{\mathbf{B}}(\beta_2)(2\kappa(F_{\mathbf{B}}(\beta_2) - 1) + \delta) - (1-p)\delta}{2 + p(F_{\mathbf{B}}(\beta_2)^2 - 2)}. \tag{3.30}$$

We find that the payoff in the asymmetric case is:

$$E[C^{(3)}]_A = (1-p)(2r^A - r^L) - 2\delta(1-p). \tag{3.31}$$

Existence conditions

In order to asses whether an interbank market will emerge as an equilibrium outcome, we both need to ensure that engaging in interbank lending is the optimal action for both banks as well as show optimality for consumers to invest in banks. The first condition establishes the optimality of interbank lending by comparing the expected payoff in the interbank market case to the payoff in the non-lending benchmark case (cf. Eq. 3.20). The demarcation criterion for the optimality criterion is: $E[C^{(3)}]_A \geq E[C^{(3)}]_B$. Then we check under what conditions the participation constraint (cf. Eq. 3.10) is met so that banks will exist in the economy, because it is better for consumers to invest in banks rather than store their wealth themselves. This constraint is met when $E[C^{(3)}]_A \geq 1$. The borrowing constraint (cf. Eq. 3.11) needs to be met for an interbank market to emerge.

It follows directly that the borrowing constraint (cf. Eq. 3.11) is met only if

$$r^A \geq 2\delta. \tag{3.32}$$

We now turn to the optimality condition and the participation constraint. Similar to the symmetric equilibrium, one needs to distinguish two cases when examining the optimality condition. If the return from the productive technology is lower than the costs of running a bank ($\kappa < \delta$), it is optimal for banks to engage in interbank lending when:

$$r^{L^*} \leq r^A - \delta. \tag{3.33}$$

For cases in which the return from the productive technology is larger or equal to the costs of running a bank ($\kappa \geq \delta$), the optimality condition is:

$$r^{L^*} \leq r^A + \frac{p(2\delta - \kappa) - \delta}{1-p}. \tag{3.34}$$

For the participation constraint to be met we need to have

$$r^{L^*} \leq 2(r^A - \delta) - \frac{1}{1-p}. \tag{3.35}$$

Because the LHS of the participation constraint and the optimality condition are the same we can reduce the two conditions into one by focusing only on the larger of the two. In case of $\kappa \geq \delta$ the participation constraint is binding if:

$$2(\delta - r^A) + \frac{1}{1-p} \geq \frac{(1-2p)\delta + p\kappa - (1-p)r^A}{1-p} \tag{3.36}$$

or

$$\frac{1 + \delta - p(\kappa - r^A) - r^A}{p(\delta - \kappa)} \geq 0. \tag{3.37}$$

In case of $\kappa < \delta$ the participation constraint is binding if:

$$2(\delta - r^A) + \frac{1}{1-p} \geq \delta - r^A \tag{3.38}$$

or

$$\frac{1}{(1-p)(\delta - r^A)} \geq -1. \tag{3.39}$$

If the participation constraint is not binding, the optimality condition is the demarcation criterion. The above conditions also imply that in the absence of interbank lending the participation constraint would not be met and thus no banks would exist.

Proof of existence

We prove the existence of parameter configurations that permit the interbank market equilibrium to arise by considering some parameters in their limit case. Remember that

$$r^{L^*} = \frac{2\pi p(\delta - 2\kappa)\tan^{-1}\left(e^{\frac{a(b-2)}{2b}}\right) + 8\kappa p \tan^{-1}\left(e^{\frac{a(b-2)}{2b}}\right)^2 + \pi^2(p-1)(\delta - 2r^A)}{2\pi^2(p-1) - 4p\tan^{-1}\left(e^{\frac{a(b-2)}{2b}}\right)^2}. \tag{3.40}$$

We take both the costs of running a bank to their minimum $\delta \to 0$ and the default return of the productive technology to its minimum $\kappa \to 0$. It turns out that the ordering of the limits does not affect the result and we find that the equilibrium conditions of Eqs. 3.33 and 3.34 both become:

$$0 \leq r^A \left(\frac{\pi^2(p-1)}{2p \tan^{-1}\left(e^{\frac{a(b-2)}{2b}}\right)^2 - \pi^2(p-1)} + 1 \right). \tag{3.41}$$

The participation constraint (cf. Eq. 3.35) becomes

$$0 \leq \frac{1}{p-1} + r^A \left(2 + \frac{1}{\frac{2p \tan^{-1}\left(e^{\frac{a(b-2)}{2b}}\right)^2}{(p-1)\pi^2} - 1} \right). \tag{3.42}$$

We know that the participation constraint is binding whenever Eq. 3.39 is true. In the limit case this criterion becomes

$$1 \geq r^A(1-p). \tag{3.43}$$

As $r^A \geq 1+\delta$ and $0 \leq p \leq 1$ it is easy to see that there are values for p and r^A for which the optimality condition is binding as well as values for p and r^A for which the participation constraint is binding. For the proof of existence we focus on the optimality condition, i.e. any combination of r^A and p such that $r^A(1-p) \geq 1$. Given that in the limit case there are no costs to running a bank, in the absence of liability guarantees consumers will only invest in banks if their expected return is larger than their endowed wealth. In order to prove existence it suffices to show that the RHS of Eq. 3.41 is positive under some parameter values, which is equivalent to showing that there are parameter values for which

$$\frac{\pi^2(p-1)}{2p \tan^{-1}\left(e^{\frac{a(b-2)}{2b}}\right)^2 - \pi^2(p-1)} \geq -1. \tag{3.44}$$

As $0 \leq p \leq 1$ we can rewrite Eq. 3.44 as

$$\frac{-c}{c + 2p\tan^{-1}\left(e^{\frac{a(b-2)}{2b}}\right)^2} \geq -1 \tag{3.45}$$

for some arbitrary constant c.

We know that

$$2ptan^{-1}\left(e^{\frac{1(b-2)}{2b}}\right)^2 \geq 0. \tag{3.46}$$

Therefore, the lower bound of the LHS of Eq. 3.44 is -1, which means that there are parameter values for which Eq. 3.44 is true. This completes the proof.

Interbank market equilibrium

We can therefore formulate the following proposition.

Proposition 3.2.2. *In an economy with two banks and an outside probability of liability guarantees for insolvent banks, an equilibrium can exist that is marked by positive levels of interbank lending (interbank market equilibrium). In such a case banks would be of different sizes, with one bank acting as lender in the interbank market only and the other bank borrowing only and investing twice its initial size in the productive technology. Such an equilibrium emerges if the expected payoff of banks is i) larger than the payoff in the non-lending benchmark case and ii) satisfies consumers participation constraint. Formally the following conditions need to hold for an interbank market to emerge:*

1. *If* $\kappa < \delta$*:* $r^{L^*} \leq r^A - \delta$ *and* $r^{L^*} \leq 2(r^A - \delta) - \frac{1}{1-p}$.

2. *If* $\kappa \geq \delta$*:* $r^{L^*} \leq r^A + \frac{p(2\delta-\kappa)-\delta}{1-p}$ *and* $r^{L^*} \leq 2(r^A - \delta) - \frac{1}{1-p}$.

The interbank rate r^{L^*} *in such an equilibrium being*

$$r^{L^*} = \frac{2\pi p(\delta - 2\kappa)\tan^{-1}\left(e^{\frac{a(b-2)}{2b}}\right) + 8\kappa p \tan^{-1}\left(e^{\frac{a(b-2)}{2b}}\right)^2 + \pi^2(p-1)(\delta - 2r^A)}{2\pi^2(p-1) - 4p\tan^{-1}\left(e^{\frac{a(b-2)}{2b}}\right)^2}. \tag{3.47}$$

3.3 Discussion

We set out to examine whether interbank markets can exist for reasons other than regionally or temporally dispersed liquidity shocks (Allen and Gale, 2000; Cocco, Gomes and Martins, 2009; Diamond and Rajan, 2005). We consider a simple interaction between consumers, two banks that act as collective investment vehicles, and an external agent (regulator), which can guarantee the liabilities of banks. Defaults can occur in the economy because the productive technology can return a loss, and costs may exceed returns from investments in this productive technology and returns from interbank lending. While we find that it is never optimal for banks to engage in interbank lending as long as banks lend and borrow to a similar degree, even if it influences the probability to induce a government bailout, we show that an interbank market equilibrium exists in which one bank becomes a lender and the other a borrower. What is striking that even in this simple model we find interesting dynamics that generate banks of different sizes and with different balance sheet compositions. The model results are consistent with the notion of money centre banks (Craig and von Peter, 2014), a group of banks in an economy that act as an aggregator and redistributor of liquidity.

Proposition 3.2.2 shows that an interbank market equilibrium can exist. The equilibrium exists only if one bank is a lender and the other bank a borrower. Thus, the two banks in our model are engaged in a coordination game. If one considers the game a simultaneous move game, we are faced with potential coordination failures. In the absence of sunspot equilibria that may influence preferences to become either a lender or a borrower, coordination failures are possible and mixed strategy equilibria exist.

Nonetheless, the results of the chapter provide support for an emerging literature on creating voluntary exposures between counter parties. Farboodi (2014) describes an economy in which financial institutions enter lending and borrowing contracts in order to benefit from intermediation rents that arise from differential access to profitable investment opportunities. These opportunities are unknown ex-ante to financial institutions, which then strategically position themselves to gain access to investment opportunities or benefit from intermediation between funding sources and investment opportunities. Her model is in the vein of assuming regional dispersement in order to justify interlinkages between financial institutions. The model probably closest to ours is Eisert and Eufinger (2013). They argue that interbank lending can be profitable for banks because of uninsured creditors. Specifically the authors study circular lending relationships with banks based in different countries with fixed probabilities of bailout. If unsecured creditors lend to counter parties that themselves lend to counter parties in countries with a positive bailout probability, the expected return for uninsured creditors increases. What is novel and striking about our model in comparison is that structural features emerge from ex-ante identical banks. An interbank market is not a consequence of heterogeneity of banks, but rather a systemic consequence of rational bank behaviour in the presence of a regulator.

When comparing our results to others who have studied collusion or coordinated bank behaviour to shift risk to governments and take advantage of non-targeted intervention (Acharya and Yorulmazer, 2007; Eisert and Eufinger, 2013; Farhi and Tirole, 2012; Leitner, 2005) one finds some commonalities but also some differences in results. The assumption in much of these works is that banks coordinate their actions so that defaults occur contemporaneously and thus induce government intervention. In our model liability guarantees only extend to some banks and we have shown that in our model symmetric coordinated actions cannot lead to interbank lending. Still, similar to the argument presented in Farhi and Tirole (2012), and Eisert and Eufinger (2013) even uninsured banks benefit from guarantees of their counter party because it increases their expected repayment.

One limitation of the model in its current form is the inability to study the effect of non-zero bailout probabilities in conjunction with other rationales for forming interbank exposures. Both liquidity co-insurance as well as intermediation (Diamond, 1984; Farboodi, 2014; Gale and Kariv, 2007) are two known drivers of exposures. It was the objective of this chapter to provide a mechanism through which to study the effect of uncertain bailout probabilities on lending between banks in isolation. So, this specific limitation exists by design. However, one must be cautious in interpreting the results with regards to the interbank market rate. At least for any empirical test of our model one would have to integrate or control for further drivers of interbank liabilities. The model in the next chapter takes a first step in the direction of combining different drivers.

We also propose a function that allows us to model bailout uncertainties in different legal environments or at different points in time. We introduce a solution to the Sine-Gordon system as a family of functions that are both well-behaved analytically, and for which we can parametrise the uncertainty regarding a bailout-decision as well as the absolute threshold for a bailout to occur. We show that both parameters are directly relevant in determining whether an interbank market will form and characterise equilibrium interbank lending rates. Given those parameters may vary over time, our propositions lend themselves to empirical examination. Not only could the results be used to examine micro-behaviour of banks taking government-related bailout probabilities into account and linking them to the level of interbank lending of banks. It also allows us to compare different legal environments. Extensions of the simplified model could allow researchers to determine the implied bailout uncertainty and bailout threshold from the structure of interbank markets.

While it seems difficult to derive analytical solutions for a model that relaxes the assumptions of symmetric actions and homogeneity of banks, one could examine both through simulations and further seek to estimate the parameters of our model empirically. In particular, it would be interesting to see how results change if one increases the number of banks in the economy and introduces an ex-ante distribution of bank size. Moreover, extending the model into a repeated game scenario in which banks decide on their level of interbank lending and borrowing, and potentially know the payoff of their debtors and creditors, could add interesting dynamics.

Future work may also seek to model the strategic behaviour of governments directly. Currently we assume that the bailout function is fixed and only depends on the systemic importance of banks. In our model, the participation constraint of consumers ensures that when banks exist, their default is possible. It is thus not possible to avoid potential default by investing a larger proportion of assets in the storage technology. Depending on how one models the behaviour of governments, results may vary. Assuming that governments are welfare optimisers and incur some fixed costs for bailing out banks, governments could choose between bailing out banks and guaranteeing deposits. Governments then face an optimisation problem in which they weigh the returns from the productive technology against the costs of bank bailouts.

Depending on the costs, governments may prefer to only guarantee deposits, in which case no interbank market would form. However, if the returns from the productive technology exceed the costs of bailout, then governments would prefer to bail out banks rather than depositors. It seems plausible to assume that there are some fixed costs to bailing out each bank, in which case governments would prefer to bail out one bank only. In this case one should expect similar results to our model.

3.4 Conclusion

We have shown through a simple model that even in the hypothetical absence of a liquidity management or intermediation function of the interbank market, positive levels of interbank lending are an equilibrium outcome if banks of higher systemic importance receive uncertain liability guarantees. We specify the exact conditions under which lending arises and derive an interbank market rate. We have shown that besides the probability of default of a risky technology and the expected return of the technology, two parameters describing the bailout probability function influence the interest rate. We use a function that allows us to specify both the uncertainty regarding a bailout as well as a underlying threshold around which the bailout probability of a bank depend on a bank-specific measure of systemic importance.

We thus provide a basis for studying complementary drivers of interbank markets in addition to liquidity co-insurance. An interesting result of our model is its ability to produce banks of unequal size with large banks investing in risky technologies and small banks providing funding for these projects. The results in this chapter allow scholars to empirically estimate bailout uncertainties and bailout thresholds in different countries. The next chapter introduces a model of endogenous interbank network formation based on entering liquidity co-insurance contracts. We consider the role of non-zero bailout probabilities in an extension to the dynamic model in the next chapter and thereby make a first step to rigorously examining the interplay between liquidity co-insurance and an incentives for strategic positioning of banks.

Chapter 4

Coordination and Competition in the Formation of Financial Networks

Financial crises have long been studied as a result of contagious effects spreading in financial networks. Following the seminal work of Allen and Gale (2000), and Freixas, Parigi and Rochet (2000) the network structure of interbank claims, in the form of interbank deposits, liquidity co-insurance, and other co-exposures, is studied extensively to determine what structures are more likely to cause contagious adverse effects following shocks to financial systems (Acemoglu, Ozdaglar and Tahbaz-Salehi, 2015; Allen and Gale, 2000; Elliott, Golub and Jackson, 2014; Eisenberg and Noe, 2001; Gai and Kapadia, 2010; Glasserman and Young, 2015). Interbank liquidity co-insurance (Castiglionesi and Navarro, 2011; Castiglionesi and Wagner, 2013) allows banks to fulfil their role as mediators between wealth and profitable investment opportunities and thereby facilitate economic growth in a market economy. In the presence of effective liquidity co-insurance banks do not need to liquidate their investments at a loss in order to satisfy uncertain consumption demands by depositors. Interlinked financial networks thus are both a decentralised insurance mechanism against independent shocks and at the same time the cause of potential systemic failures (Diamond and Rajan, 2005). In this chapter we study the formation of bilateral liquidity co-insurance between banks and the resulting financial network of insurance claims as an example of a financial network. While the main driver of entering liquidity co-insurance contracts is the protection against liquidity shocks, we consider an extension of the model in which alternative motives are taken into account.

We generalise and extend the seminal three-period model of Allen and Gale (2000). We generalise the set-up to an arbitrary number of regions and introduce endogenous insurance link formation. We study an economy with three time periods $t = 0, 1, 2$ and n regions. Each region is inhabited by one consumer endowed with wealth and uncertain consumption preferences, and one bank with access to a profitable investment opportunity (productive technology). Consumers can only deposit their wealth with the bank in their region, while banks can interact with banks in other regions. The bank offers a deposit contract at $t = 0$ which allows the consumer to draw its wealth in either of the two future time periods. The consumer also receives a share of the profits in return for its deposit (interest). If the bank invests any portion of the deposited wealth in the productive technology and the consumer demands its deposit at $t = 1$, in the absence of liquidity co-insurance the bank would have to prematurely liquidate its investment and under our model assumptions would default.

We abandon the assumption that banks are resolved in the last period. Banks retain some profits and thus optimise their wealth rather than act on behalf of consumers, which introduces agency as argued for by Allen (2001). We study the formation of financial networks and whether self-interested banks with limited information effectively and efficiently insure against independent liquidity shocks. To be able to do so we first introduce a mechanism of liquidity co-insurance. Banks form costly bilateral insurance links that allow banks with a liquidity need to repeatedly draw on liquidity from their insurance partner. We show that in a connected insurance network with no aggregate liquidity shortfalls this insurance mechanism is effective at redistributing liquidity throughout the network. This formulation of liquidity co-insurance frees us from making assumptions regarding the distribution of shocks and connections as is the case in the Allen and Gale model, who only allow one payment to take place.

We then proceed to introduce the expected value of bank profits. Using the wealth of consumers and the charter value of banks we derive the Nash Bargaining Solution as the profit share that banks retain. We replicate the results of Allen and Gale in showing that it is optimal for competitive banks to invest the portion of the deposits in the productive technology that is optimal from the perspective of a social planner, i.e. a portion such that at an aggregate level no liquidity shortfall exists. We then introduce the liquidity co-insurance game with limited information Γ. We show that under full information in a simultaneous move, best shot version of the game multiple equilibria in pure strategies exist that can produce the socially optimal outcome. However, we further find that under limited information a unique equilibrium in mixed-strategies exists that is only a second best and has lower welfare than the social optimum.

A key challenge in understanding the formation of financial networks is to model the simultaneous evolution of strategic behaviour by self-interested banks as well as the evolution of the financial network that they are imbedded in. The strategic link formation of banks also influences the stability of the insurance network that emerges from decentralised decisions. We address this challenge by studying a dynamic version of the model in which banks are chosen at random to update their strategy in the insurance market. In order to study evolutionarily stable states and steady states of the dynamic model we introduce a notion of stability of the insurance network, as well as the Gini co-efficient as a measure of inequality for the system. We show through stochastic simulations that the unique equilibrium of the static model constitutes a stable state in the dynamic model, but also that it is not evolutionarily stable. Once one player deviates from the equilibrium strategy the distribution of bank strategies moves towards one of the equilibria in pure strategies. While the evolutionarily stable state produces higher overall welfare, the insurance network is less stable and inequality between regions is greater.

Finally, we study an extension of the dynamic model that introduces bank-specific factors influencing the profit share banks can retain. We assume that up to a certain stability of the insurance network banks with a larger number of insurance links are considered more important and have a higher likelihood of being bailed out. The bailout probability, or rather the bailout probability as perceived by depositors, is influenced both by the importance of a bank to the insurance network, as well as the stability of the network itself. Banks can increase their bailout probability by strategic link formation. However, if too many banks pursue such a strategy, at some point each bank is perceived to be equally likely to be bailed out. The increased link formation also makes the structure of the insurance network more stable, which in return reduces the benefits from this strategy to banks. As long as differential numbers of insurance links exist, some banks can retain a larger profit share than others. We show through stochastic simulations that non-zero bailout probabilities lead to a higher stability of the insurance network and a larger average number of insurance links. Interestingly, such an effect produces the same welfare as the unique constrained optimal equilibrium of the static model.

The chapter proceeds as follows. We begin by reviewing related works before introducing the liquidity co-insurance game with endogenous link formation. We introduce the insurance mechanism first and then formally introduce the static version of our game Γ. We identify both pure-strategy and mixed-strategy equilibria and study their welfare. We then formulate a dynamic version of the game and study its stable states. Lastly, we study the extension of the dynamic model by introducing a non-zero bailout probability. We conclude with a discussion.

4.1 Related works

Our work is related to at least four strands of literature. The first is a set of papers that follow Allen and Gale (2000) (henceforth AG) in studying interbank markets as a mechanism to absorb liquidity shocks, and link formation in that context. The second strand studies interbank links as a consequence of balance sheet optimisation, or some sort of imitation mechanism. The third set of papers studies endogenous interbank link formation as a consequence of financial intermediation. The fourth is a set of related works in the tradition of coordination games on graphs and game-theoretical network formation games in the tradition of Jackson and Wolinsky (1996).

Hüser (2015) provides a recent and comprehensive overview of the state of the interbank networks literature, including a review of network formation games and a review of the work on the role of interbank network structures for systemic risk. Several models have been put forward that build on AG and sometimes on Eisenberg and Noe (2001), to study interbank linkages as a form of insurance against liquidity shocks. In the literature on liquidity co-insurance (cf. Brusco and Castiglionesi, 2007 or Castiglionesi and Wagner, 2013 for instance) it is usually assumed that banks with uncertain liquidity needs exchange deposits or credit lines prior to the realisation of a liquidity shock. In terms of modelling assumptions, closest to our work are probably Nash (2015) and Castiglionesi and Navarro (2011). Both study a n-region version of the AG model, Nash in a three-period model and Castiglionesi and Navarro in a five-period model. Castiglionesi and Navarro assume banks of a-priori different sizes who exchange deposits and choose between a safe and risky technology. They study interbank insurance in the form of credit lines and as a function of the technology-choice of banks. Moreover, profit-maximising banks choose the number of costly insurance links in order to increase the probability of being connected to a bank with a liquidity surplus in case of need. Using pairwise stability (Jackson and Wolinsky, 1996) they show that in the light of counter party risk, banks of the same type prefer to link, which leads to core-periphery networks.

Nash allows banks to enter either binding or non-binding co-insurance contracts and to choose an effort level which influences the likelihood of experiencing a liquidity shock caused by the returns of the productive technology. Their model follows the tradition of mechanism design and shows that non-binding credit lines increase the incentive for increased screening, while full insurance increases the amount invested in the productive technology. An additional liquidity shock is exogenous and only hits one bank at $t = 1$. The focus of the work is more on the propagation of shocks than on the endogenous link formation. Nonetheless, Nash considers an extension in which pre-existing long-term debt may force a bailout, which could be seen as a motivation for the extension of our model.

In our model we assume that interbank insurance contracts are contingent on the presence of a private liquidity insurance mechanism that can clear the market for liquidity needs. This assumption of conditional exchange of liquidity, rather than an ex-ante exchange of deposits as in AG, is motivated by the fact that interbank credit lines are frequently renegotiated. Besides Nash (2015) others have studied conditional liquidity co-insurance or the renegotiation of such contracts. David and Lehar (2014, 2015) show that renegotiation is common in interbank debt contracts, which is consistent with a view of risk-sharing contracts that are renegotiated once uncertainty is resolved. Leitner (2005) shows that the possibility of renegotiation increases the incentive for private sector bailouts. Erol and Vohra (2014) study a three-period model of n nodes of which each pair can form a link to partake in a joint undertaking. The profitability of an undertaking is determined randomly at the second period of the model. In the third period individual nodes decide whether or not to default based on the combined profitability of all projects. Profitability is generated through forming links, but nodes take system-wide failures into account and form structures that are robust against such failures. The more safe the underlying system, the denser the interconnectivity and risk that failures spread. Their model is similar to Blume et al. (2013), even though default is modelled as a strategic choice rather than an endogenous outcome.

A set of papers studies interbank lending and borrowing decisions as an optimisation problem rather than insurance. Banks are endowed with wealth or are deposit-takers and lend optimally given the risk of contagion and ex-ante returns. Halaj and Kok (2014) study a tradeoff between the costs and expected returns of interbank loans in a model with full information and exogenously fixed total lending volume. Georg (2014) studies the tradeoff between exposure to contagious failure and access to investment opportunities. Hojman and Szeidl (2006) study a model in which banks derive payoffs from interacting neighbours but links are costly.[34] Cabrales, Gottardi and Vega-Redondo (2014) model a tradeoff between risk sharing and exposure to contagious failure. Such works are closely linked to more general models on the link between exposure to contagious network effects and benefits from forming links (Blume et al., 2013; Erol and Vohra, 2014). A small number of papers study agent-based models with exogenous link formation probabilities (Cohen-Cole, Patacchini and Zenou, 2010) or preferential lending and borrowing based on trust (Iori et al., 2015). Even though not part of the recently published paper (cf. Acemoglu, Ozdaglar and Tahbaz-Salehi, 2015) the endogenous interbank lending model in Acemoglu, Ozdaglar and Tahbaz-Salehi (2013) considers endogenous link formation in which banks can post a set of borrowing and lending rates together with the amounts of lending and borrowing offered at those rates. In their generalisation of AG and Eisenberg and Noe (2001), banks form links in a three-step process. Each bank first posts for each other bank a mapping between an amount of interbank loans it is willing to provide and the rate at which it is willing to lend that amount. After all public postings are observed banks can withdraw offers. In a third step banks choose their borrowing level which determines lending levels. Lastly, Castiglionesi et al. (2014) show that in models with heterogenous bank capital a negative correlation between bank capital and interbank market activity exists.

Several models exist that study interbank lending as a consequence of financial intermediation. Wegner (2014) studies a model in which banks are endowed with access to productive technologies with different returns. Two banks form links if an interest rate exists at which the participation constraint of both banks are met. Similarly, Farboodi (2014) studies intermediation chains of debt-financed banks, which exist

---

[34] An extension in their model uses myopic best-response (Kandori, Mailath and Rob, 1993; Young, 1993*b*).

because of differential access to profitable investment opportunities while Di Maggio and Tahbaz-Salehi (2014) study intermediation to connect capital to investment opportunities.[35] Farboodi shows that through strategic borrowing and the presence of intermediation spreads, inefficient networks can form that resemble core-periphery networks. [36] Lastly, a small set of papers study interbank lending as a consequence of benefits from trade. Cohen-Cole, Patacchini and Zenou (2015) study a model in which banks link randomly with the player that offers the highest benefit, in't Veld, van der Leij and Hommes (2014) study core-periphery structures as a consequence of interbank links forming to divide surpluses from trade, and Brusco and Castiglionesi (2007) study a model in which interbank lending occurs to take advantage of regional differences in liability.

Finally, our work is related to traditional network formation models following Jackson and Wolinsky (1996) and Jackson and Watts (2002*b*), as well as to coordination games on graphs. The recent review paper by Jackson and Zenou (2014) provides an overview of the state of the games on graph literature and the network formation literature. While we do not evoke pairwise stability (Jackson and Wolinsky, 1996) as an equilibrium concept, the dynamic version of our model allows banks to form and break links with each other. We do study the efficiency and welfare of the equilibrium networks (Dutta and Mutuswami, 1997; Jackson and Wolinsky, 1996). Our modelling assumptions are closer to models of unilateral link formation, which were put forward by Goyal and Vega-Redondo (2005), Bramoullé et al. (2004), and Bala and Goyal (2000) amongst others. However, the dynamic formulation of our liquidity co-insurance game is close to the concept of improving paths as introduced

---

[35] Babus (2011) is another example of a model in which banks lend and borrow because of intermediation.

[36] On empirical evidence on core-periphery networks in financial markets see Craig and von Peter (2014) and for a model of core-periphery emergence in networks see Hojman and Szeidl (2008).

by Jackson and Watts (2002*b*).

In our model banks form costly insurance links. Banks thus have an incentive to have as few insurance links as possible. At the same time, the insurance links are conditional on all banks being connected to each other through at least one path. Conceptually our model is thus related to coordination and interaction games on graphs, specifically local public goods games. There is a long tradition of studying the effect of graph structures on games (Jackson, 2010). Ballester, Calvó-Armengol and Zenou (2006) study a model of local interaction games on networks, which has been influential in subsequent work in this area. Agents obtain a payoff if a certain aggregate threshold in effort levels by its neighbours is reached.[37] The costs of exerting maximal effort to achieve the benefit threshold are lower than the benefit from this action. Therefore, isolated agents would always exert this effort. However, if agents are linked to each other and the efforts by neighbours act as substitutes the optimal effort level is reduced. This is in line with our cheap insurance assumption (Assumption 4.2.2), which makes sure that costs are not an artificial limit to the number of insurance links formed.

Bramoullé and Kranton (2007) study public goods games on networks in a setting where benefits from a publicly beneficial effort are non-excludable in network links. They show that the existence and type of equilibria are linked to the underlying network structure. Galeotti et al. (2010) provide a summary of this type of network game in which agents exert costly efforts that are either substitutes or complements. They show that when agents have complete information about the network which they are embedded in, that there is a multiplicity of equilibria in a Bayesian learning framework. What is interesting is that they show how local information reduces mul-

---

[37] A typical example of this sort of situation is information gathering or research and development.

tiplicity of equilibria and usually leads to the identification of unique Nash equilibria. Similar to our model, even under local information, agents are assumed to know the distribution of agent degrees in the network.[38] Bramoullé, Kranton and D'Amours (2014) generalise this line of work into a framework that captures a large class of interaction games both for (local) complements and substitutes.

4.2 Liquidity co-insurance with endogenous link formation

We build our model on a generalisation of the AG set-up.[39] We study an economy with n regions and three time periods $t = 0, 1, 2$. Each region is inhabited by one representative consumer and one bank. Consumer-bank interactions are limited to each region, while transactions between banks of different regions are permissible. A consumer in region i is endowed with one unit of a consumption good $b_i = 1$. As in AG and Diamond and Dybvig (1983) consumers can be of two types and are either patient or impatient. Patient consumers value consumption only at $t = 2$, while impatient consumers value consumption only at $t = 1$. Following AG it is assumed that the consumer utility function is well-behaved, i.e. twice continuously differentiable, increasing, and strictly concave, and that consumers are risk-neutral. At $t = 0$ consumers do not know whether they are patient or impatient, their type is revealed at $t = 1$. Only the probability $0 < \omega < 1$ that a consumer is impatient is known at $t = 0$.[40]

Moreover, two technologies exist in the economy. Both banks and consumers

---

[38] Also see Galeotti and Vega-Redondo (2011). Boncinelli and Pin (2012) use stochastic stability to overcome this multiplicity of equilibria.

[39] The AG model itself is based on Diamond and Dybvig (1983) and Allen and Gale (1998).

[40] This assumption is equivalent to the proportion of impatient agents in a continuum of consumers in AG.

have access to a storage technology. The storage technology returns one unit of the consumption good for each unit invested in the previous period. In addition to the storage technology, each bank can invest in a productive technology (asset) in the first period (at $t = 0$) which returns $R > 1$ units of the good after two periods (at $t = 2$) but nothing when prematurely liquidated (at $t = 1$). Contrary to AG, we assume that banks are a going concern and are not dissolved at $t = 2$. Banks keep a part of the returns of the productive technology as profits and share the rest with their depositors as interest. The assumption that banks have exclusive access to the investment technology and depositors are not mobile captures the notion of a bank-specific charter value. Demsetz, Saidenberg and Strahan (1996) distinguish two types of charter value, market-related and bank-related. Despite the findings of Keeley (1990) which document a decline of a market-related charter value, the value of firm-specific lending and borrowing relationships is documented by Petersen and Rajan (2012) and appears to be persistent. In fact, the broader literature on relationship-lending documents a monetary value of bank-specific factors.[41] We assume that all banks are endowed with the same charter value $\bar{c}$.

At $t = 0$ banks in different regions can enter mutual liquidity co-insurance contracts. These contracts give both parties a conditional right to draw liquidity from the other party if they have a liquidity shortfall at $t = 1$. The contract is conditional on the effectiveness of the insurance market (denoted by $\theta \in \{0, 1\}$). We introduce θ together with the insurance mechanism in the next section. We denote the presence of a bilateral liquidity co-insurance as a link between two banks or $l_{ij} = l_{ji} = 1$. The absence of an insurance link is denoted by $l_{ij} = l_{ji} = 0$. Because a bank cannot insure

---

[41] Cf. Cocco, Gomes and Martins (2009) for evidence of preferential trading relationships in Portugal, Bräuning and Fecht (2012) in Germany, Akram and Christophersen (2012) for Norway, or Afonso, Kovner and Schoar (2013) for evidence of relationship lending in the US overnight market and a positive effect on interest rates at times of distress. Iori et al. (2015) explain Italian e-MID data that document preferential trading relationships through a model of trust.

itself, we have $l_{ii} = 0$. We examine the totality of interbank insurance contracts as a financial network in which each bank i is a node and part of the set of nodes, or $i \in N$. The liquidity co-insurance network is thus the graph $\mathbf{g}(N, \mathbf{L})$ with $\mathbf{L}$ the $n \times n$ adjacency matrix with typical element $l_{ij} \in \{0, 1\}$. For convenience we also write $\mathbf{g}(\mathbf{L})$. If the insurance market is effective ($\theta = 1$) then both parties to an insurance link incur costs $\delta(d_i)$ for the d_i links they maintain, which are payable at $t = 2$. Throughout the model we assume that these costs are small, but weakly increasing in the number of insurance links d_i. We formalise this assumption below.

In the remainder of the section and the next we introduce and study a liquidity co-insurance game with limited information.

Definition 4.2.1 (Liquidity co-insurance game with limited information)**.** *Define the liquidity co-insurance game with limited information as the following n-player game* Γ*:*

$$\Gamma = \{C, N, V(\sigma), \sigma, \mathbf{I}\}, \tag{4.1}$$

where C the set of consumers, N the set of banks, $V(\sigma)$ the payoff function, $\sigma = \{\Sigma \cup \hat{\Sigma}\}$ the strategy set available to banks with Σ the pure strategies and $\hat{\Sigma}$ the mixed strategies, and I the information set.

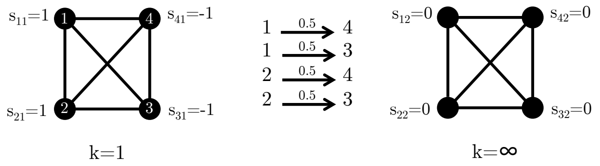
For each region both consumers and banks have a participation constraint. Banks only form when these are met. Banks then choose their strategies and the payoff V_i in region i is split between banks and consumers according to the outcome of Nash bargaining (Nash, 1950). We denote the profit share retained by banks as $0 \leq \nu_i \leq 1$. We first introduce the insurance mechanism before discussing the payoff function and optimal bank behaviour. Then we formally introduce the liquidity co-insurance game and find several equilibria in pure strategies under complete information and identify a unique Nash Equilibrium in mixed strategies. Lastly, we introduce welfare considerations and compare the welfare of the mixed-strategy competitive equilibrium with the welfare of the pure-strategy equilibria and the social optimum.

4.2.1 Clearing of the liquidity co-insurance market and its effectiveness

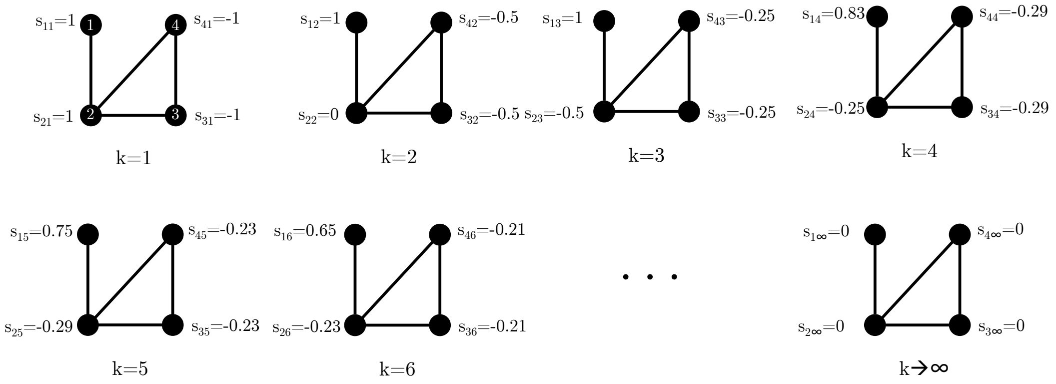
We introduce the mechanics of the liquidity co-insurance market as well as the definition of its effectiveness. Banks enter liquidity co-insurance contracts before knowing either their own liquidity need or the needs, or surpluses, of their counter parties. Both parties to an insurance contract have the right to draw liquidity if a liquidity need exists at $t = 1$. A liquidity need arises when an impatient consumer demands one unit of the consumption good, but the bank has invested only a proportion $w_i < 1$ of the deposits in the storage technology. Let $s_i = w_i - 1$ denote such a liquidity shock. Thus, the effectiveness of the insurance market depends on all bilateral insurance contracts that are formed in the economy, as well as on the aggregate liquidity in the market and the process by which claims are settled. We model the clearing of the interbank market as a series of liquidity requests.

We show in proposition 4.2.1 that this process of value flows to banks with liquidity shortfalls clears the interbank market provided the insurance is effective, in the sense of the definition below, the presence of no aggregate liquidity shortfall and a connected insurance network. Let $s_i \in \{s_+, s_-\}$ be the liquidity surplus of each bank i at $t = 1$. We thus have the liquidity surplus vector $\mathbf{s}$ at $t = 1$ which contains the liquidity surplus or need of all banks in the system. If banks form, bank liquidity at $t = 1$ is either positive at $s_+ = w_i > 0$ or they have a liquidity need $s_- = w_i - 1 < 0$. Define the $n \times 1$ column vector $\mathbf{s}_k = [\hat{s}_{1k}\hat{s}_{2k} \ldots \hat{s}_{nk}]'$ of liquidity needs. Let $\tilde{\mathbf{L}} = \mathbf{L}^n$, the

a) Example of fully-connected liquidity co-insurance network (effective)



b) Example of connected liquidity co-insurance network (effective)



c) Example of disconnected liquidity co-insurance network (ineffective)

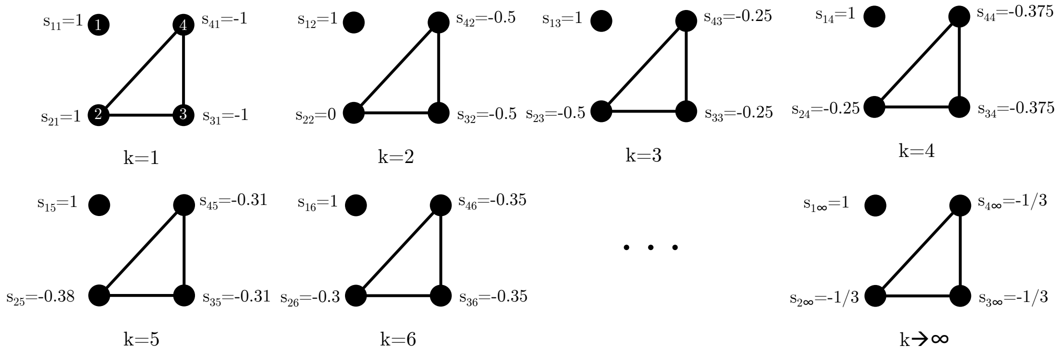


Figure 4.1: Mechanics of liquidity co-insurance network

The figure shows three stylised examples of liquidity co-insurance networks and the mechanics of the market clearing mechanism described in this section. In all networks no aggregate shortage of liquidity exists. Panel a) corresponds to the complete market structure as introduced in AG, panel b) shows a connected network that is effective as insurance, panel c) shows a disconnected network that is ineffective as insurance.

nth-power of the adjacency matrix of network $\mathbf{L}$. Each entry $\tilde{L}_{ij}$ shows the number of paths from node i to j of length up to n. Given there are n banks in the system, if value can flow from one bank to another, any path must be shorter than n steps. We can now formalise the definition of effectiveness:

Definition 4.2.2 (Effectiveness of liquidity co-insurance). *We define the effectiveness of liquidity co-insurance θ as a function of the financial network $\mathbf{g}(\mathbf{L})$ and the liquidity needs vector $\mathbf{s}$:*

$$\theta\left(\mathbf{g}(\mathbf{L}), \mathbf{s}\right) = \begin{cases} 1 & \textit{if} \quad \sum_{i=1}^{n} s_i \geq 0 \land \tilde{L}_{ij} \geq 1 \; \forall \; i \neq j \\ 0 & \textit{otherwise} \end{cases}. \tag{4.2}$$

We proceed to show that under these conditions all liquidity needs can be privately satisfied. We define a series $(\hat{\mathbf{s}})_k$ for $k = 1, 2, \ldots$ that generates as its limit the net liquidity needs of banks after insurance. Before specifying the series we need to define some matrices. Define $\hat{\mathbf{B}}_k = \{1 \; \forall \; i \in N : \hat{s}_{i,k} < 0; 0 \; \forall \; i \in N : \hat{s}_{ik} \geq 0\}$ as the $n \times 1$ indicator vector for the presence of a liquidity need. It is one for each negative element of $\hat{\mathbf{s}}_{\mathbf{k}}$ and zero otherwise. Let $\mathbf{E_i}$ be the $n \times n$ matrix of zeros with 1 at its $(i,i)th$ element and $\mathbf{e}_i$ the $1 \times n$ row vector of zeros with 1 at its $(1,i)th$ position. Let matrix $\mathbf{D}_k$ be the square indicator matrix for liquidity needs whose ith diagonal element is one if i has a liquidity need and otherwise zero:

$$\mathbf{D}_k = \sum_{i=1}^{n} \mathbf{E}_i \hat{\mathbf{B}}_k \mathbf{e}_i. \tag{4.3}$$

Thus, $\mathbf{D}_k$ is the $n \times n$ matrix with $(D_k)_{ii} = 1$ for all i with $\hat{s}_{i,k} < 0$. Based on this indicator matrix and the adjacency matrix of the insurance network $\mathbf{L}$ we can now define the insurance claims matrix:

$$\mathbf{C}_k = \mathbf{L}\mathbf{D}_k\theta, \tag{4.4}$$

with $C_{i,j,k}$ the typical element of $\mathbf{C}_k$. The insurance claims matrix $\mathbf{C}_k$ contains the permissible liquidity flows based on the liquidity insurance matrix $\mathbf{L}$. Note the presence of θ, which prohibits insurance claims if the market is ineffective or $\theta = 0$ pursuant to the contingency of the insurance contract.

Let $\mathbf{\Lambda}_k \in \mathbb{M}_{1\times n}$ be the row vector containing the number of counter parties per bank:

$$\mathbf{\Lambda}_k = \sum_{i=1}^{n} \mathbf{C}_{i,\star,k}, \tag{4.5}$$

where $\mathbf{C}_{i,\star,k}$ denotes the i-th row of $\mathbf{C}_k$. To avoid division by zero define $\tilde{\mathbf{\Lambda}}_k$ with elements $\tilde{\Lambda}_{1,j,k} = \max\{\Lambda_{1,j,k}, 1\}$. Moreover, let $\hat{\mathbf{\Lambda}} \in \mathbb{M}_{1\times n}$ with $\hat{\Lambda}_{1,j,k} = \min\{\Lambda_{1,j,k}, 1\}$ be the indicator vector for whether a counter party exists. Assuming that banks have no preferred counter parties, we assume that liquidity claims are split evenly. We can thus obtain the transfers between all banks as the transfer matrix $\hat{\mathbf{D}}_k = [\hat{D}_{ij,k}]_{i,j=1}^{i,j=n}$:

$$\hat{\mathbf{D}}_k = \sum_{i=1}^{n} (-1)\mathbf{E}_i \left(\hat{\mathbf{s}}_k \circ \hat{\mathbf{\Lambda}}_k\right) \tilde{\Lambda}_{1,i,k}^{-1} \tag{4.6}$$

where $\circ$ denotes the Hadamard product.

We can now describe the series of market clearing:

$$\hat{\mathbf{s}}_{k+1} = \hat{\mathbf{s}}_k + \underbrace{\tilde{\mathbf{\Lambda}}_k' \circ \hat{\mathbf{\Lambda}}_k' \circ \hat{\mathbf{D}}_k}_{\text{Liquidity claim transfers}} - \underbrace{\mathbf{C}_k\hat{\mathbf{D}}_k}_{\text{Insurance payments}}. \tag{4.7}$$

This process converges when all liquidity needs are satisfied. Assuming there is some lower bound on possible transfers, the process stops once no more transfers are made. The process is said to converge at $\tilde{k}$ which is the first k for which $\sum_{i=1}^{n} \sum_{j=1} \hat{D}_{ij,k} \leq a$ for some small constant a.

Definition 4.2.3 (Insurance market clearing)**.** *The insurance market clearing is the series* $(\hat{\mathbf{s}})_k$ *as defined in Eq. 4.7 with* $\hat{\mathbf{s}}_1 = \mathbf{s}$ *as the starting condition,* $\mathbf{L}$ *the adjacency matrix of the liquidity co-insurance network, and* θ *the effectiveness of the liquidity co-insurance market as in Definition (4.2.2). The insurance market is said to have cleared after* $\tilde{k}$ *steps.*

Figure 4.1 shows three examples of liquidity co-insurance networks and their clearing, in which, for the sake of expositional ease, we assume $s_- = -1$ and $s_+ = 1$. We define the net liquidity surplus after insurance as the outcome of the converged series, or as

$$\tilde{\mathbf{s}} \equiv \left\{ \hat{\mathbf{s}}_k | k : \sum_{i=1}^{n} \sum_{j=1}^{n} \hat{D}_{ij,k} \leq a \right\}, a \to 0. \tag{4.8}$$

We can now formulate the following proposition about the effectiveness of the interbank market.

Proposition 4.2.1 (Clearing of liquidity co-insurance market)**.** *(i) If the co-insurance network is connected, i.e. there exists a path from each bank* i *to each other bank* j*, and no aggregate shortfall of liquidity in the economy exists when the insurance market clearing happens, then the liquidity needs of all banks are satisfied* ($\tilde{s}_i \geq 0 \; \forall \; i \in N$) *after the insurance market clearing as in Definition 4.2.3.*

$$\sum_{i=1}^{n} s_i \geq 0 \wedge \tilde{L}_{ij} \geq 1 \; \forall \; i \neq j \implies \tilde{s}_i \geq 0 \; \forall \; i \in N. \tag{4.9}$$

(ii) Moreover, the market converges for any finite number of banks n*. Letting* $\alpha > 0$

and $\beta > 0$ *be some integers, potentially large, we have:*

$$n \leq \alpha \implies \tilde{k} \leq \beta. \tag{4.10}$$

Proof To give some intuition, the liquidity co-insurance network is effective if excess liquidity can flow from any region in the economy to any other region in the economy. Formally, we can prove Proposition 4.2.1 by contradiction. Starting with the first part of the proposition, suppose that any $\tilde{s}_{ik} < 0$. By assumption there is no aggregate shortage of liquidity, so $\sum_{i=1}^{n} s_i \geq 0$. It thus follows that there must exist a $\tilde{s}_{jk} > 0$ for $j \neq i$. It follows from the iterative clearing described in Eq. 4.7 that $\hat{s}_{j,k+1} \leq \hat{s}_{j,k}$ for any $\hat{s}_{j,k} \geq 0$ and $\hat{s}_{i,k+1} \leq 0$ for any $\hat{s}_{i,k} < 0$. We know the graph is connected, so the maximum distance between i and j is n (maximum path length). Thus, after a maximum of n iterations of the process a liquidity claim will be made on j so that $\hat{s}_{j,k+1} < \hat{s}_{j,k}$. Given the process has converged we know by Eq. 4.8 that $\lim_{\epsilon \to 0} \hat{D}_{ij,k} = 0 \; \forall \; i, j \in N$. Therefore, $\hat{s}_{j,k+1} = \hat{s}_{j,k}$, which is the contradiction.

The second part of the proposition follows immediately from placing an upper bound α on the maximum path length. For any bank i with a liquidity surplus $\hat{s}_{i,k} > 0$ if there exists a liquidity need in the system $\hat{s}_{j,k} < 0$ for some j, it follows that $\hat{s}_{i,k+\alpha} < \hat{s}_{i,k}$. Given that α is a finite integer, it will take a finite time for all banks $i \in N$ to either have no liquidity need or a surplus after no more than an arbitrarily large but finite number of steps β: $\lim_{\epsilon \to 0} \hat{s}_{i,k} \geq 0$ for all $i \in N$ for some $k \leq \beta$.

The market clearing process is of course only an algorithmic approximation. Also note that β may be large and convergence can thus be slow for large n. In reality, a centralised, or at least a coordinated clearing or settlement mechanism could determine the net payments required between all banks (Eisenberg and Noe, 2001), which would shorten the clearing process. However, the clearing process seems useful as a modelling assumption, because it provides a mechanism for a decentralised liquidity co-insurance market that is vulnerable to free-riding and depends on the participation of a sufficiently large number of banks in the economy for it to be effective.

This definition allows us to evaluate the effectiveness of a static co-insurance market given a liquidity need vector. In the remainder of this chapter we usually assume that there is no aggregate liquidity shortfall but rather study dynamics of link formation of banks and examine whether effective insurance is formed.

4.2.2 Bank profits

At $t = 0$ consumers decide whether they deposit their endowed good with their bank in return for a deposit contract or hold the storage technology. Banks decide what proportion of the unit of the good to invest in the storage technology and what proportion to invest in the productive technology. AG have shown that, in the absence of aggregate liquidity shocks and in the absence of costs for maintaining insurance links, the socially optimal allocation is both feasible and optimal in a decentralised interbank market. As stated above $0 \leq w_i \leq 1$ denotes the proportion of the wealth invested in the storage technology. Banks also form the liquidity co-insurance network at this stage. The actions of bank i in the network formation game are denoted by $\mathbf{A}_i \in \mathbf{A}$ and formally discussed below. The pure strategies of bank i are denoted by $\Sigma_i \in \Sigma$, where $\Sigma_i = \{\mathbf{A}_i, w_i\}$. We write the collection of bank strategies as $\boldsymbol{\Sigma} = \{\Sigma_1, \Sigma_2, \ldots, \Sigma_n\}$. We can write the expected undiscounted value of a bank

$V_i(\Sigma_i)$ as:

$$V_i(\Sigma_i) = \underbrace{\theta\left(\mathbf{g}(\mathbf{L}), \mathbf{s}\right)\left[(1-w_i)Rb_i + w_ib_i - \delta(d_i)\right]}_{\text{Effective liquidity insurance}} + \underbrace{b_i\left(1-\theta\left(\mathbf{g}(\mathbf{L}), \mathbf{s}\right)\right)\left[w_i + (1-\omega)\left(1-w_i\right)R\right]}_{\text{Ineffective liquidity insurance}}. \tag{4.11}$$

Because of $b_i = 1$ for all i in the static analysis of the model we obtain:

$$V_i(\Sigma_i) = \theta\left(\mathbf{g}(\mathbf{L}), \mathbf{s}\right)\left[(1-w_i)R + w_i - \delta(d_i)\right] + \left(1-\theta\left(\mathbf{g}(\mathbf{L}), \mathbf{s}\right)\right)\left[w_i + (1-\omega)\left(1-w_i\right)R\right], \tag{4.12}$$

where $d_i = \sum_{j=1}^{n} l_{ij}$.[42]

We assume risk-neutral consumers and that banks offer deposit contracts that allow consumers to draw one unit of the consumption good at $t = 1$. Their total utility from depositing their wealth with the bank is $(1 - \nu_i)V_i$, where ν_i is the share of V_i retained by bank i, which consists both of their deposit and an interest payment. It is of course possible that in the absence of effective insurance and an underinvestment in the storage technology by banks, consumers receive less than their deposit at $t = 1$, for which case we assume limited liability so that the bank is liquidated and loses her charter value. The depositor receives all assets in this case. We further assume that banks are a going concern and thus place a premium on their charter value, which makes them risk averse. Thus, in autarky banks would always hold the storage technology in order to avoid default with probability $1 - \omega$ at $t = 1$. Given the representative consumer does not yet know whether she will be patient or impatient at $t = 1$, she will deposit her wealth with the bank if the expected value of depositing with the bank satisfies her participation constraint.

We use Nash bargaining (Nash, 1950) to obtain a share ν_i of V_i that is retained

---

[42] The dynamic extension of the model is considered in section 4.3 and allows for the consumer wealth to grow and shrink.

by the bank. This share depends both on the outside option of a bank $o_i(\bar{c})$ as well as a scaling factor $\psi_i > 0$ based on bank-specific factors. For the static analysis we assume that bank-specific factors are absent, or $\psi_i = 1$. We later introduce ψ_i as a form of status or systemic importance to the stability of the financial network (liquidity co-insurance network). The outside option is the capital of a bank, which is the endowed charter value plus any retained profits. In the static model there are no retained profits, therefore $o_i(\bar{c}) = \bar{c}$.

Pursuant to the Nash Bargaining Solution (NBS), we maximise the following expression. The outside option for the representative consumer is to use the storage technology and thus b_i with $b_i = 1$ in the static case. The outside option of banks is their charter value, or in the dynamic case its charter value plus retained profits, scaled by a factor ψ_i for bank-specific factors:

$$\max_{0 \leq \nu_i \leq 1} \underbrace{((1-\nu_i)V_i(\Sigma_i) - b_i)}_{\text{representative consumer}} \underbrace{(\nu_i V_i(\Sigma_i) - \psi_i o_i(\bar{c}_i))}_{\text{bank } i} . \tag{4.13}$$

The second derivative of this expression is always smaller than zero ($-2V_i^2$), which means the following ν_i^* is the NBS:

$$\nu_i^*(\psi_i) = \begin{cases} 1 & \text{if } \frac{\psi_i o_i(\bar{c}_i) + V_i(\Sigma_i) - b_i}{V_i(\Sigma_i)} \geq 2 \\ 0 & \text{if } V_i(\Sigma_i) \leq b_i - \psi_i o_i(\bar{c}_i) \ \cdot \\ \frac{1}{2} \frac{\psi_i o_i(\bar{c}) + V_i(\Sigma_i) - b_i}{V_i(\Sigma_i)} & \text{otherwise} \end{cases} \tag{4.14}$$

It follows that the consumer participation constraint is

$$\begin{cases} 0 \geq b_i & \text{if} \quad \frac{\psi_i o_i(\bar{c}_i) + V_i(\Sigma_i) - b_i}{V_i(\Sigma_i)} \geq 2 \\ V(\Sigma_i) \geq b_i & \text{if} \quad V_i(\Sigma_i) \leq b_i - \psi_i o_i(\bar{c}_i) \quad \cdot \\ V_i(\Sigma_i) \geq b_i + \psi_i o_i(\bar{c}_i) & \text{otherwise} \end{cases} \tag{4.15}$$

and the bank participation constraint

$$\begin{cases} V(\Sigma_i) \geq o_i(\bar{c}_i) & \text{if} \quad \frac{\psi_i o_i(\bar{c}_i) + V_i(\Sigma_i) - b_i}{V_i(\Sigma_i)} \geq 2 \\ 0 \geq o_i(\bar{c}_i) & \text{if} \quad V_i(\Sigma_i) \leq b_i - \psi_i o_i(\bar{c}_i) \quad \cdot \\ V_i(\Sigma_i) \geq o_i(\bar{c})(2 - \psi_i) + b_i & \text{otherwise} \end{cases} \tag{4.16}$$

Because $\bar{c}_i > 0$ it is clear that the participation constraints impose a limit on feasible equilibria. We have $b_i - V_i(\Sigma_i) \leq \psi_i o(\bar{c}) \leq V_i(\Sigma_i) + b_i$ and for the static case where $b_i = 1$ we have $1 - V_i(\Sigma_i) \leq \psi_i o(\bar{c}) \leq V_i(\Sigma_i) + 1$.

4.2.3 Optimal investment in storage technology

For the optimal choice of the storage technology w_i^* we make the following assumption.

Assumption 4.2.1 (No aggregate liquidity shocks)**.** *In the economy there exists an even number of n regions and at $t = 1$ exactly ωn random regions have impatient consumers and $(1 - \omega)n$ have patient consumers. We further assume that n is large enough so that both the number of patient and impatient regions are integers.*

At $t = 1$ the consumer in each region realises whether she is patient or impatient. As the realisation of whether consumers are patient or impatient is a Bernoulli trial with probability ω for impatient, for a large enough and even number of independent regions the realised number of impatient consumers is exactly ωn and $(1-\omega)n$ patient consumers. In equilibrium we thus have liquidity needs of $\omega n(w_i^* - 1)$ and a surplus of $(1-\omega)nw_i^*$. For the liquidity co-insurance to be effective we thus need $\omega n(w_i^* - 1) + (1-\omega)nw_i^* \geq 0$, which yields $w_i^* = \omega$.

Assuming a given liquidity co-insurance network and that the participation constraints of both banks and consumers are met it is straightforward to show that $w_i^* = \omega$ is the equilibrium action for all banks and no bank can unilaterally change their action to improve their payoff. For instance, assume the complete market structure as in AG and shown in Figure 4.1 panel a). AG show that in the absence of aggregate liquidity needs the first-best allocation of wealth between the storage technology and investment technology can be achieved in a decentralised banking sector, both through complete and incomplete markets. This result is reproduced by our model and to an extent generalised to the n-region setting. For a large enough number of regions and sufficiently high return from the productive technology, any static connected liquidity co-insurance network leads to the first best allocation. Of course the main result of AG is not that both incomplete as well as complete market structures can provide liquidity co-insurance in the absence of aggregate liquidity shocks, but that incomplete market structures are more fragile in the presence of an ex-ante zero-probability event of an aggregate liquidity shortfall. AG argue that for a large number of regions, contagion can be avoided for small shocks in a complete market structure, while in an incomplete system it can lead to contagion. Before we proceed to study equilibrium existence formally, we first introduce the network formation game and thereby finalise the description of the strategies available to banks at $t = 0$.

4.2.4 Liquidity co-insurance game and static equilibria

In addition to choosing the optimal investment amount in the storage technology, the co-insurance market constitutes a n-player simultaneous move (best-shot) game in which banks decide for each other bank in the system whether to initiate an insurance link. Thus, the action set available to each bank is $A = \{L, NL\}$, where L denotes the action to initiate a link and NL to not form a link. The link formation action vector of a bank consists of a $(n-1) \times 1$ vector $\mathbf{A}_i$ with action $A_{ij} \in A$ for all $j \neq i$. Only if $A_{ij} = \{L\}$ and $A_{ji} = \{L\}$ is a co-insurance link formed. The strategy of each bank can thus be fully characterised by $\Sigma_i = \{\mathbf{A}_i, w_i\} \in \Sigma$. Before discussing the optimal strategy with limited information about the action of other banks, briefly assume banks have full information including the strategies of all other banks $\{\Sigma_j | j \neq i\}$.

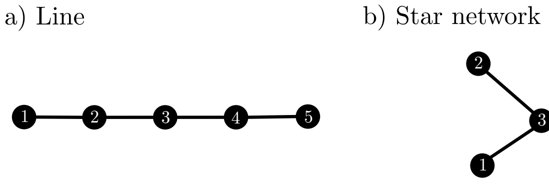


Figure 4.2: Equilibrium insurance networks under full information ($n = 5$)

The figure shows the line and the star network as two examples of an effective liquidity co-insurance network with a minimum number of links ($n-1$)*.*

Throughout we assume that insurance links are costly. We do not further specify the type of costs incurred by banks. The cost function is meant to model administrative and search costs for entering insurance links, which are likely decreasing in the total number of links formed, as well as costs for monitoring counter parties (cf. Nash, 2015). Depending on the overall structure of the insurance network, it seems plausible that banks with a higher number of insurance links would find it more difficult to find counter parties and thus incur higher costs for insuring themselves. Throughout our model we assume a linear cost function that assumes banks are incurring fixed costs for entering insurance. In practice the trade-off between costs and benefits from insurance is likely to determine whether effective insurance can form and what insurance networks form. In our model we would like costs to be non-restrictive in order to not artificially influence equilibrium selection. It is therefore helpful to make one assumption regarding the cost of forming links.

The costs of forming links are meant to model that banks prefer forming fewer links to forming more links, but at the same time they should not limit the ability of banks to form complete insurance networks. In this assumption we follow the work of Galeotti et al. (2010) and others on public goods provision in networks. They assume that in the absence of the public good it is optimal for players to exert all effort themselves, but they choose to exert less effort if their neighbours are already exerting an effort. The participation constraint of consumers already (weakly) prevents any equilibria in which no liquidity co-insurance is formed. We therefore make the following non-restrictive assumption:

Assumption 4.2.2 (Cheap insurance)**.** *The maximum cost for liquidity co-insurance is such that the equilibrium payoff* $V_i(\Sigma_i^*)$ *for* $w_i^* = \omega$ *is greater under effective insurance* ($\theta = 1$) *than under ineffective insurance* ($\theta = 0$) *regardless of the number of insurance links* $d_i \leq (n-1)$ *formed, or*

$$\frac{\delta(n-1)}{R(\omega - \omega^2)} \leq 1. \tag{4.17}$$

Provided that effective liquidity insurance exists, banks maximise their value by minimising the number of insurance links they maintain. There are many insurance networks that form Nash Equilibria, two of which are depicted in Figure 4.2 for $n = 5$. The first such network structure is a line. One strategy set that leads to a line is the following. If bank $i = 1$ plays $A_{12} = \{L\}$ and all other $A_{1j} = \{NL\}$. Bank

$i = n$ chooses $A_{n,n-1} = \{L\}$ and all other $A_{nj} = \{NL\}$. All other banks i play $A_{i,i-1} = \{L\}$, $A_{i,i+1} = \{L\}$, and $A_{ij} = \{NL\}$ for all other j. Let this strategy set be denoted by $\mathbf{A}'$. Under these strategies $n-1$ co-insurance links form between the n banks, which makes all banks connect to one or two neighbours to form a fictitious line. The second such network structure is a star. This market structure forms if one bank i, $i = 3$ in the example in Figure (4.2), plays $A_{ij} = \{L\}$ for all $j \neq i$ and all other banks $\neg i$ play $A_{\neg i,i} = \{L\}$ and $A_{\neg i,j} = \{NL\}$ for all $j \neq i$. Let this strategy set be denoted by $\mathbf{A}''$. Note that both the line and the star have the minimum number of edges required for a connected graph.

If the participation constraints for banks and consumers are met (Eqs. 4.16 and 4.15 respectively) and an insurance network forms, it is easy to show that it is optimal for banks to play one of the above link formation strategies together with $w_i^* = \omega$. Each bank is strictly better off under effective liquidity co-insurance. Because of the Cheap Insurance Assumption 4.2.2, this statement is true even for the central hub in the star network. If any bank broke, or rather does not form, one of its links, the liquidity insurance would be ineffective in the sense of definition 4.2.2 and the bank as well as all other banks are strictly worse off. Forming additional links would increase costs $\delta(d_i)$ and thus reduce the payoff of each bank. If any bank invested less than ω in the storage technology, the insurance mechanism would also be ineffective. Increasing w_i above ω is suboptimal given $\partial V(w_i)/\partial w_i < 0$ for all R, ω, and w_i. Thus, because no player can unilaterally deviate from their equilibrium action without being strictly worse off, the two strategy profiles described above are strict Nash Equilibria in the sense of

$$\forall\ i\ \in\ N, \Sigma_i \in \Sigma : \nu_i^*(\psi_i) V_i(\Sigma_i^*, \Sigma_{\neg i}^*) > \nu_i^*(\psi_i) V(\Sigma_i, \Sigma_{\neg i}^*), \tag{4.18}$$

where $\Sigma_i^* = \{\mathbf{A}_i^{'}, \omega\}$ or $\{\mathbf{A}_i^{''}, \omega\}$.

The following proposition summarises this result:

Proposition 4.2.2 (Existence of multiple pure-strategy equilibria). *Under the assumptions of cheap insurance (4.2.2), no aggregate liquidity shocks (4.2.1), and complete information multiple pure-strategy Nash Equilibria exist if the participation constraints of consumers (Eq. 4.15) and banks (Eq. 4.16) are met and the parameters are such that forming banks is feasible:*

$$1 - \frac{1}{2}V_i(\Sigma_i^*) \geq o_i(\bar{c}_i, \psi_i) \leq \frac{1}{2}V_i(\Sigma_i^*) + 1. \tag{4.19}$$

In any pure-strategy equilibrium strategy $\Sigma_i^* = \{\mathbf{A}_i, \omega\}$ banks always choose to invest ω in the storage technology and consumers deposit their endowed wealth.

Many scholars have studied the effect of sparsely connected financial networks (Acemoglu, Ozdaglar and Tahbaz-Salehi, 2015) or incomplete network structure (cf. AG), and have examined the general effect of the structure of financial networks on their stability (Glasserman and Young, 2015). We examine the stability of equilibrium networks in the next section. However, we first address a challenge that, besides many others, has been addressed and identified by Galeotti et al. (2010).[43] Under full information and only considering pure-strategy equilibria, a large number of feasible Nash Equilibria exists. Moreover, the assumption of full information in a decentralised liquidity co-insurance market, especially when considering a large number of regions, appears to be too generous. For what follows we thus make the following assumption.

Assumption 4.2.3 (Local and global information). *Players in the liquidity co-insurance formation game know the structure of the game such as the payoff function,*

---

[43] Also cf. Bramoullé and Kranton (2007) and Bramoullé, Kranton and D'Amours (2014).

the cost of maintaining insurance links, the insurance market clearing mechanism, the strategy set, the number of regions, the likelihood of an impatient consumer, all charter values, the return available from their productive technology, and the strategy set available to all players. However, they have no information about the actions of other players. Thus their information set $I_i \in \mathbf{I}$ *at* $t = 0$ *is the following:*

$$I_i = \{V(\Sigma), \delta(d_i), (\hat{\mathbf{s}})_k, n, \bar{c}_j \ \forall \ j \in N, R_i, \Sigma\}. \tag{4.20}$$

This assumption reflects that in the interbank market banks will only have local information about the action of other banks. For instance, when a bank initiates a link with another bank it will obtain information about the strategy of that bank, but not about the strategy of other banks. In a repeated version of this game we may assume that banks have some knowledge about the global properties of the formed network, for instance whether it is connected and thus effective, but only at $t = 1$. Galeotti et al. examine how limiting the information available in network games, can actually help with the equilibrium selection problem. One strategy would be to never link to other banks, i.e. $\mathbf{A}_i^{NL} = \left\{ A_{ij} = \{NL\} \ \forall \ j \neq i \right\}$. It has already been shown that in the absence of liquidity co-insurance banks would put all of the deposits in the storage technology, which means that both the consumer and the bank participation constraints would not be met. Alternatively, banks could choose to form links with all other banks, $\mathbf{A}_i^{L} = \left\{ A_{ij} = \{L\} \ \forall \ j \neq i \right\}$. Because we assume cheap insurance costs (assumption 4.2.2) this strategy is feasible. Of course it is not a Nash Equilibrium, because players could unilaterally deviate by forming less links without causing the co-insurance network to be disconnected.

There is a unique Nash Equilibrium in mixed strategies. Players choose the probability p_i to form a link and then choose an action set at random that contains precisely the number of link initiations they want to offer, but with counter parties chosen at random. Let $|\{\dots\}|$ denote the norm of a set. The set $\{A_{ij} : A_{ij} = \{L\}\}$ is the set of all actions that are initiating a link $(\{L\})$. Therefore, $\{\mathbf{A}_i : |\{A_{ij} : A_{ij} = \{L\}| = p_i n\}$ is the set of all action vectors $\mathbf{A}_i$ that contain exactly $p_i n$ $\{L\}$ actions. To randomise, players choose each action vector from the set $\{\mathbf{A}_i : |\{A_{ij} : A_{ij} = \{L\}\}| = pn\}$ with equal probability $1/|\{\mathbf{A}_i : |\{: \mathbf{A}_i : A_{ij} = \{L\}\}| = pn\}|$ and all other available action vectors with zero probability. For large n, this strategy is equivalent to flipping a coin with weight p_i for forming a link $\{L\}$ and $(1 - p_i)$ for not forming a link $(\{NL\})$ for each A_{ij} in $\mathbf{A}_i$. We can thus denote i's strategy as $\hat{\Sigma}_i = \{p_i, w_i\} \in \hat{\Sigma}$. The following definition summarises the strategic choice problem faced by banks in the liquidity co-insurance market.

Definition 4.2.4 (Liquidity co-insurance game with limited information)**.** *Define the liquidity co-insurance game with limited information as the following n-player game* Γ*:*

$$\Gamma = \{C, N, V(\sigma), \sigma, \mathbf{I}\}, \tag{4.21}$$

where $\sigma = \{\Sigma \cup \hat{\Sigma}\}$ *and* C *the set of consumers in the economy.*

Because players cannot coordinate their actions, there is no natural way to choose any one specific action vector. However, given the information set of players, there is an optimal p_i $\forall$ i. By choosing a fixed p_i the network formation game is equivalent to a random graph model. Specifically, it is equivalent to a random graph model in the formulation of Gilbert (1959). Each link between two vertices of a graph exist with a given probability. In our model this probability for each edge (link) between i and j is $p_i p_j$. Erdös and Rényi (1959, 1960, 1961) provide seminal work in this area of Poisson random graph models, which, contrary to Gilbert, assume networks to form sequentially by randomly adding one edge at a time from a fixed number of edges. Erdös and Rényi (1960) prove a threshold function $t(n) = log(n)/n$ that determines the probability of a graph being connected. For any (arbitrarily small) $\epsilon > 0$ the probability of a connected graph tends to zero for large n if the probability of link formation is $t(n) - \epsilon$. Similarly, the probability of a connected graph tends to one for large n if the probability of link formation is $t(n) + \epsilon$. Theorem 7.3 of Bollobás (2001) provides a proof based on the results of Stepanov (1969, 1970*a*,*b*) and Kovalenko (1971), showing that these results hold for both generative models of random graphs.[44]

Therefore, for $n \rightarrow \infty$ and $\epsilon \rightarrow 0$ we find a mixed strategy equilibrium in which each bank offers to form a link to any counter party with probability $p_i^* = \sqrt{log(n)/n + \epsilon}$. Playing p_i^* yields a connected graph with probability tending to one. Importantly, the results by Erdös and Rényi (1960) also imply that playing $\{L\}$ with any $p_i < p_i^*$ would yield a disconnected graph with probability tending to one. Playing $\{L\}$ with any probability $p_i > p_i^*$ would not increase the likelihood of effective insurance but would increase the costs of insurance to banks, given that $\partial\delta(d_i)/\partial p_i > 0$. As shown above it is strictly optimal for banks to form effective insurance. Thus, we find the unique Nash Equilibrium strategy $\hat{\Sigma}_i = \{p_i^*, \omega\}$.

Proposition 4.2.3 (Unique mixed-strategy equilibrium)**.** *Under the assumptions of cheap insurance (4.2.2), no aggregate liquidity shocks (4.2.1), and limited local and global information (4.2.3) a unique mixed-strategy Nash Equilibrium exists if the participation constraints of consumers (Eq. 4.15) and banks (Eq. 4.16) are met and*

---

[44] Chapter 4 in Jackson (2008) provides an accessible overview of these results including some proofs.

the parameters are such that forming banks is feasible:

$$b_i - V_i(\Sigma_i) \leq o_i(\bar{c}) \leq V_i(\Sigma_i) + b_i. \tag{4.22}$$

In the liquidity co-insurance game with limited information Γ *(Definition 4.2.4) the mixed-strategy* $\hat{\Sigma}_i^* = \{p_i^*, \omega\}$ *is the unique Nash Equilibrium action for all banks. As in any pure-strategy equilibrium banks choose to invest* ω *in the storage technology. Moreover, we have the equilibrium probability of bank* i *to initiate a link with any bank* j *is:*

$$p_i^* = \sqrt{log(n)/n + \epsilon}. \tag{4.23}$$

We established that

$$\forall\ i\ \in\ N, \hat{\Sigma}_i \in \hat{\Sigma} : \psi_i \nu_i^*(\psi_i) V_i(\hat{\Sigma}_i^*, \hat{\Sigma}_{\neg i}^*) > \psi_i \nu_i^*(\psi_i) V(\hat{\Sigma}_i, \hat{\Sigma}_{\neg i}^*) \tag{4.24}$$

and it follows from the participation constraint that consumers will deposit their endowed wealth.

4.2.5 Welfare of static equilibria

We briefly examine the welfare W of the static equilibria. Assuming that both banks and consumers are risk-neutral, the total welfare in the economy is simply the sum of consumer wealth and bank wealth. Because banks and consumers share the value generated by banks, in equilibrium (i.e. under effective insurance, $\theta = 1$, and investing $w_i = \omega$) the welfare is simply the total value generated by banks:

$$W^* = \sum_{i=1}^{n} V_i = \sum_{i=1}^{n} (1 - \omega)R + \omega - \delta(d_i). \tag{4.25}$$

We compare the welfare under the socially optimal allocation to the welfare under the unique decentralised liquidity co-insurance market equilibrium. We have shown that under full information the first-best (FB) allocation is possible under which an insurance network with $n-1$ links forms. In these equilibria no bank can unilaterally deviate from its actions and the total welfare is

$$W^{FB} = n\left[(1-\omega)R + \omega\right] - (n-1)\delta(1) - \delta(n-1). \tag{4.26}$$

In a decentralised liquidity co-insurance market with limited information we expect banks to form an average of ${p^*}^2 n$ links or $d_i = log(n) + \frac{\epsilon}{n} \geq 1 \ \forall \ n \geq 10$. We thus obtain

$$W^{SB} = n\left[(1-\omega)R + \omega - \delta(log(n))\right] \tag{4.27}$$

for sufficiently low ϵ. Therefore, we find that the welfare of the competitive outcome is smaller than the social optimum when

$$n\delta(\log(n)) \geq (n-1)\delta(1) + \delta(n-1). \tag{4.28}$$

For a simple linear cost function where each link incurs a fixed cost we find the threshold to be

$$\frac{n\log(n)}{2(n-1)} \geq 1. \tag{4.29}$$

Because the limit of the LHS is infinity, for large n we can conclude that for a large number of regions the welfare of the competitive outcome is lower than the social optimum.

Proposition 4.2.4 (Inefficiency of insurance in decentralised liquidity co-insurance game Γ). *Given a large number of regions, the welfare of the unique mixed-strategy* *equilibrium of the liquidity co-insurance game under local information is lower than the socially optimal welfare attainable under complete information or coordination by a social planner.*

$$W^{FB} > W^{SB}. \tag{4.30}$$

This result is somewhat inconsistent with AG who find that the first-best allocation of wealth is attainable in a competitive banking sector. While the allocation to the productive technology in our model is the first best ($w_i = \omega$), the liquidity co-insurance is not. We have shown above that this is due to the costs of insurance, which AG ignore because liquidity co-insurance is modelled as an exchange of interbank deposits. In the absence of costs the welfare of the competitive equilibrium would be the same as the social optimum. Thus the welfare W^{SB} in our model is lower than the first best in AG by the costs of links required to form an effective liquidity co-insurance network. This statement similarly applies to the first-best allocation. Assuming zero costs for liquidity co-insurance, we would weakly generalise the AG results to a n-region setting and thus get rid of the assumption in AG that regions have perfectly correlated liquidity shocks. Of course this is not much of a contribution given our results rely on the number of regions in the economy to be large.

Others have extended the traditional AG model to a n-region context. These works include Castiglionesi and Navarro (2011), and Nash (2015), even though both differ significantly from our modelling assumptions. Castiglionesi and Navarro study an economy with five periods in which heterogenous banks first establish credit links and then offer deposit contracts. Nash focuses on whether or not banks choose to monitor their investment and thus increase its payoffs, therefore focusing on the incentive to exert a costly effort arising from link formation. Castiglionesi and Navarro also find that introducing costly links impairs the socially optimal insurance outcome. Galeotti et al. (2010) offers important insights into the effect of network structure on public goods games with local information. Many others of course have studied the effect of costs on efficient link formation in a general network context, amongst others by Blume et al. (2013), Cabrales, Calvó-Armengol and Zenou (2011), Goyal and Vega-Redondo (2005), Jackson and Wolinsky (1996), and Jackson and Watts (2002*b*). We could show that the unique Nash Equilibrium in the liquidity co-insurance formation game creates an incomplete market structure rather than the complete market structure. Nonetheless, the complete market structure is a feasible outcome, albeit being a strictly dominated strategy and thus not attainable in a decentralised market. This result has implications for the fragility of the liquidity co-insurance and the vulnerability to random shocks. We discuss this aspect further in the next section.

In the remainder of the chapter we consider two extensions to this model, which allow us to study the stability of the financial network as well as welfare in a dynamic model. First, we study a dynamic version of the link formation model. This formulation allows us to incorporate two key features. So far we have assumed that banks have no information about their immediate local environment such as the strategies of the banks to which they offer to initiate an insurance link. How do our results change when banks can make their, potentially probabilistic, actions conditional on the link formation probability of other banks. Specifically, we introduce banks of different types that differ in their probability of initiating links, with each type having a strategy contingent on the type of the bank they meet. We think of these static differences in link formation probabilities as differences in the business model of banks. Furthermore, extending the model to a dynamic context also allows us to study the fragility of the liquidity co-insurance network in equilibrium and to identify evolutionarily stable states (Foster and Young, 1990; Hamilton, 1967; Maynard Smith and Price, 1973).

Second, based on the dynamic formulation of the model we introduce an alternative incentive for banks to act in the liquidity co-insurance market. We assume that if the interbank network is comparatively fragile, and some banks in the network are more important to the stability of the network than others, then these banks can increase their profit share because of this systemic importance. The effect is small for stable networks such as the complete market structure but large for fragile networks in which the removal of just a few banks would lead to an ineffective insurance market. Thus, in addition to choosing σ^* to maximise $V_i(\sigma)$, banks further choose σ^* to maximise ν_i^*. We introduce a measure for ψ_i and a systemic risk premium ρ to model this effect.

4.3 Evolutionary link-formation game

The evolutionary version of the liquidity co-insurance game Γ condenses the three-period static model into one time step. We maintain the assumption of banks as financial intermediaries. While banks can co-invest their wealth alongside with consumers, they cannot just invest their own wealth in the productive technology. At each time step one randomly-selected bank updates her strategy in the light of the distribution of strategies of all other banks. We limit the strategy set available to banks and introduce the notion of stability of the insurance network as well as inequality in the economy. We use stochastic simulations to study the evolution of welfare, the distribution of bank strategies, stability, and inequality in the economy.

4.3.1 Evolution of consumer and bank wealth

In the absence of effective liquidity co-insurance ($\theta = 0$), an impatient depositor can lead to the bankruptcy of a bank. In the case of bankruptcy, the consumer takes her losses, and the bank is replaced with a new bank, which again has the fixed charter value $\bar{c}$. This is consistent with an assumption of limited liability of banks and a new market entrant taking over region i in which the bankruptcy occurred. We study a dynamic formulation of the model that evolves in discrete time $t = 0, 1, 2, \dots$ by condensing the three time periods of the static model into one time step. Banks and consumers thus play a repeated version of the static game.

The wealth of the consumer in region i is denoted by $b_{i,t}$ with $b_{i,0} = 1 \ \forall \ i \in N$. The capital of bank $i \in N$ denoted by $o_{i,t}$, and it consists of the charter value, some sort of intangible goodwill value each bank is endowed with, and retained profits. Therefore, we have $o_{i,0} = \bar{c} \ \forall \ i \in N$ and can describe the evolution of bank capital. Let X_y be the realisation of a random variable that is identically and independently distributed (iid) with $Pr(X_y = 1) = y$ and $Pr(X_y = 0) = (1 - y)$. Following from Eq. 4.11 the realised bank value in each period $\hat{V}_{i,t}(\sigma^*_{i,t}, X_\omega, \theta_t)$ becomes:

$$\hat{V}_{i,t}(\sigma^*_{i,t}, X_\omega, \theta_t) = \theta_t\left(\mathbf{g}_t(\mathbf{L}_t), \mathbf{s}_t\right) b_{i,t}\left[(1-\omega)R + \omega - \delta(d_{i,t})\right] + \\ b_{i,t}\left(1 - \theta_t\left(\mathbf{g}_t(\mathbf{L}_t), \mathbf{s}_t\right)\right)\left[\omega + (1 - X_\omega)(1-\omega)R\right]. \quad (4.31)$$

For the stochastic simulations, we further need to assume a cost function. We assume the simplest possible cost function, which is a linear function with a fixed cost $\hat{\delta}$ for each insurance link formed, i.e. $\delta(d_{i,t}) = \hat{\delta} d_{i,t}$. Throughout the simulations the following cost is used:

$$\hat{\delta} = 0.8\frac{\omega + (1-\omega) * R - 1}{n}, \quad (4.32)$$

which ensures that the cheap insurance assumption is fulfilled.[45]

We distinguish two cases for the evolution both of consumer wealth and bank capital. The first is the case in which either the participation constraint of the consumer or the participation constraint of the bank in a region is not met. In that case no banks form and the wealth remains unaltered, or $o_{i,t+1} = o_{i,t}$ and $b_{i,t+1} = b_{i,t}$. In the second case participation constraints are met and banks form. Banks and consumers divide $\hat{V}_{i,t}(\sigma^*_{i,t}, X_\omega, \theta_t)$ according to the NBS $\nu^*_{i,t}(\psi_{i,t})$. If no effective insurance forms ($\theta_t = 0$), a region has an impatient consumer ($X_\omega = 1$), and the investment in the storage technology is insufficient to satisfy consumer demand ($\omega[b_{i,t} + o_{i,t}] < bi, t$). The bank goes bankrupt and the consumer obtains all remaining assets of the bank. If the liquidity co-insurance is effective or consumers are patient, then banks and consumers divide the value $\hat{V}$ pursuant to the NBS (cf. Eq. 4.14):

$$\nu^*_{i,t}(\psi_{i,t}) = \begin{cases} 1 & \text{if } \frac{\psi_{i,t} o_{i,t} + V_{i,t} - b_{i,t}}{V_{i,t}} \geq 2 \\ 0 & \text{if } V_{i,t}(\sigma_{i,t}) \leq b_{i,t} - \psi_{i,t} o_{i,t} \\ \frac{1}{2} \frac{\psi_{i,t} o_{i,t} + V_{i,t}(\sigma_{i,t}) - b_{i,t}}{V_{i,t}(\sigma_{i,t})} & \text{otherwise} \end{cases}, \tag{4.33}$$

where $V_{i,t}(\sigma_{i,t})$ is as in Eq. 4.11 the expected value of the investment decision. Thus, the evolution of bank wealth is described by

$$o_{i,t+1} = \begin{cases} \bar{c} & \text{if } \theta_t = 0 \wedge X_\omega = 1 \wedge b_{i,t} \geq \omega(o_{i,t} + b_{i,t}) \\ \nu^*_{i,t}(\psi_{i,t}) \hat{V}_{i,t}(\sigma^*_{i,t}, X_\omega, \theta_t) & \text{if } X_\omega = 0 \vee \theta_t = 1 \vee b_{i,t} \leq \omega(o_{i,t} + b_{i,t}) \end{cases}. \tag{4.34}$$

---

[45] The choice of the specific cost term influences the simulation results with regards to the distribution of strategies in the stable state, but does not change results qualitatively. The cost function is thus not further discussed.

Consumer wealth evolves accordingly:

$$b_{i,t+1} = \begin{cases} \omega(b_{i,t} + o_{i,t}) & \text{if} \quad \theta_t = 0 \wedge X_\omega = 1 \wedge b_{i,t} \geq \omega(o_{i,t} + b_{i,t}) \\ \Big(1 - \nu^*_{i,t}(\psi_{i,t})\Big)\, \hat{V}_{i,t}(\sigma^*_{i,t}, X_\omega, \theta_t) & \text{if} \quad X_\omega = 0 \vee \theta_t = 1 \vee b_{i,t} \leq \omega(o_{i,t} + b_{i,t}) \end{cases} . \tag{4.35}$$

4.3.2 Dynamic link formation

The order of events is the same in the evolutionary version of the model as in the static case. At the beginning of each time step consumers deposit their wealth with banks if their participation constraint is met and banks choose which links to initiate. The participation constraints are as in the static model (cf. Eqs. 4.15 and 4.16). If the participation constraints are met, banks choose their strategy $\tilde{\Sigma}_{i,t} = \{p_{i,t}(\phi_{i,t}), \omega\}$ and initiate links with a given probability.[46] Contrary to the static case, the link formation probability is restricted to a set of strategies and banks can condition their action on the strategy of banks they interact with. We distinguish three bank strategies. $\phi_{i,t} = A$ denotes aggressive banks, $\phi_{i,t} = E$ denotes equilibrium banks, and $\phi_{i,t} = F$ denotes free-rider banks. Each of these bank strategies determines the link formation probability, which is bank-specific and dependent on the strategy of the counter party as well as on the distribution of strategies. The A type suggests to form a link with every other type. The E type plays the unique equilibrium probability for random matching, would never link with a free-rider, and chooses one aggressive bank at random to link with. The F type forms only one link, and only with an aggressive type. We denote the different types by $\phi_{i,t} \in \{A, E, F\}$ and accordingly the link formation probability as $p_{i,t}(\phi_{i,t})$. This restriction models differences in the

---

[46] We have already shown that for banks to exist, the optimal investment in the storage technology is $w_i = \omega \; \forall i \in N$. It follows independently from the assumption of cheap insurance and the effectiveness of the liquidity co-insurance.

business model of banks, which banks revise at irregular time intervals.

Therefore, the link formation probabilities are as follows. For aggressive type A banks we have $p_{i,t}(\phi_{i,t} = A) = 1$. For equilibrium type E banks we have:

$$p_{i,t}(\phi_{i,t} = E) = \begin{cases} 0 & \text{for} \quad \phi_{j,t} = F \\ p^* = \sqrt{\log(n)/n + \epsilon} & \text{for} \quad \phi_{j,t} = E \\ \frac{1}{|\{i \in N : \phi_{i,t} = A\}|} & \text{otherwise} \end{cases} \cdot \tag{4.36}$$

E banks never link with free-riders and play the equilibrium probability $p*$ when interacting with other E types, but if there exists more than one A type, they choose one A bank at random to form a link with. The notation for $\phi_{j,t} = A$ is thus slightly inaccurate. This can be thought of as a sort of insurance against a growing number of F banks in the economy. For free-rider type F banks we have:

$$p_{i,t}(\phi_{i,t} = F) = \begin{cases} 0 & \text{for} \quad \phi_{j,t} = F \\ 0 & \text{for} \quad \phi_{j,t} = E \\ \frac{1}{|\{i \in N : \phi_{i,t} = A\}|} & \text{for} \quad \phi_{j,t} = A \end{cases} \cdot \tag{4.37}$$

Again, the notation is slightly inaccurate. Free-rider banks choose one A bank at random and form a link with it. If no A bank exists, no links are initiated.

Each bank knows its strategy, but only knows the distribution of strategies in the economy. Persistence of social behaviour has been documented in other contexts (Saramaki et al., 2014). The update probability of a given bank is $\lambda = 1/n$ (Szabó and Fáth, 2007). This is consistent with banks updating their business models at irregular times. When banks update their strategy they play best-response given the distribution of link formation strategies in the economy. Jackson and Watts (2002*b*) show that this process leads to stable graphs. Let $\tilde{\boldsymbol{\Sigma}}_t$ denote the vector of bank strategies at t and $\tilde{\boldsymbol{\Sigma}}_{\neg i,t}$ the vector of all bank strategies by all banks other than the bank i chosen to update its strategy. Then the best-response function $BR_{i,t}(\tilde{\boldsymbol{\Sigma}}_{\neg i,t})$ is to choose $\tilde{\Sigma}_i$ to maximise $\nu^*_{i,t}(\psi_{i,t})V(\tilde{\Sigma}_{i,t}, \tilde{\boldsymbol{\Sigma}}_{\neg i,t})$. Given the static equilibrium results it is always optimal to play $w_i = \omega$. Thus, the best-response function determines a bank's choice of $\phi_{i,t}$ given the distribution of link formation strategies of all other banks in the system.

$$BR_{i,t}(\tilde{\boldsymbol{\Sigma}}_{\neg i,t}) = \{\tilde{\Sigma}_{i,t} \in \tilde{\Sigma} : \max \nu^*_{i,t}(\psi_{i,t})V(\tilde{\Sigma}_{i,t}, \tilde{\boldsymbol{\Sigma}}_{\neg i,t})\}. \tag{4.38}$$

In some simulations we allow for an error rate ϵ. which denotes the probability that a bank chooses a strategy at random (Blume, 1995; Young, 1998).

4.3.3 Stability of liquidity co-insurance network

We can study stability as a function of random removal of banks from the liquidity co-insurance system. This removal from the insurance market is equivalent to banks renegotiating the insurance contract or simply entering non-binding insurance contracts, which is a common occurrence (David and Lehar, 2015; Nash, 2015; Zawadowski, 2013). Before discussing the results of the stochastic simulations, we introduce two further measures to describe the economy: the concept of stability of the liquidity co-insurance network as a measure of fragility of the economy and the Gini co-efficient as a measure for inequality. The fragility of the financial network depends on the likelihood that under some random shock the liquidity co-insurance network would become ineffective. The effectiveness of the insurance depends solely on the aggregate liquidity shock, which under equilibrium actions of banks in our model is always absent, and on whether graph $\mathbf{g}_t$ is connected or not. AG model shocks as a liquidity shortfall that hits one region and has an ex-ante probability of zero. A lender of last resort can correct liquidity shortfalls, even if it comes at a cost for banks (cf. Acharya and Merrouche, 2012, Acharya, Gromb and Yorulmazer, 2012, Freixas, Martin and Skeie, 2011, Freixas, Parigi and Rochet, 2000). We model the well-documented drying up of liquidity in financial systems in distress or liquidity hoarding (Acharya and Skeie, 2011; Afonso, Kovner and Schoar, 2011; Gale and Yorulmazer, 2013; Gai and Kapadia, 2010) as banks withdrawing from the interbank market.

In our model, the effectiveness of the liquidity co-insurance relies on the connectedness of the interbank market. We can thus study the stability of the interbank market as a function of the number of banks to be removed from the network for it to become disconnected.[47] We define the stability of the network as a probabilistic measure: in expectation, how many insurance links need to be removed from the insurance network for it to become disconnected. Let

$$R_t = \{\# \text{ edges to remove from } \mathbf{g}_t : Pr(\{\mathbf{g}_t \text{ is disconnected}\}) \to 1\} \leq \frac{1}{2}n(n-1). \tag{4.39}$$

A conservative definition of R_t considers the minimum number of links that are needed for a connected insurance network to exist, or $n-1$. We then have:

$$E[R_t(\mathbf{g}_t)] = \underbrace{\frac{1}{2}\sum_{i=1}^{n} d_{i,t}}_{\#\text{ Edges}} - (n-1). \tag{4.40}$$

We can define stability $S_t \in (0,1)$ as the ratio of $E[R_t]$ to the maximum number of

---

[47] Brintrup et al. (2011) show that the robustness of the Toyota supply chain network is closely linked to the degree of suppliers. The removal of a random suppliers would not threaten the robustness of the network, whereas the removal of a high-degree supplier would threaten the robustness of the network.

links to delete $\frac{1}{2}n(n-1)-(n-1)$. We obtain[48]

$$S_t = \frac{\sum_{i=1}^{n} d_{i,t} - 2(n-1)}{n^2 - 3n + 2}. \tag{4.41}$$

This stability measure does not capture any structural elements of the network and we discuss this limitation later. However, it captures well the fact that in an insurance network that relies on connectedness, the more redundant links exist between parts of the insurance network, the more stable the insurance market is.

We are also interested in studying the equality between regions. To do so we simply use the Gini co-efficient defined as follows:

$$G_t = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} |[o_{i,t} + b_{i,t}] - [o_{j,t} + b_{j,t}]|}{2 \sum_{i=1}^{n} \sum_{i=1}^{n} o_{i,t} + b_{i,t}}. \tag{4.42}$$

4.3.4 Simulation results

Figure 4.4 shows the simulation results. All simulations are stochastic and initialised with a distribution of bank strategies. We initiate the simulation with all banks playing the equilibrium strategy E. Thus, banks form links with the equilibrium probability of the static equilibrium. After 1000 time steps we introduce a small error

---

[48] The threshold for connectedness is well known for random graphs and has been established as a limit result for large n by Erdös and Rényi (1961). Also cf. section 4.2.4 and Theorem 7.3 of Bollobás (2001). In a random graph with n nodes, the threshold for connectedness is $t(n) = \frac{n}{2}\log n$ number of links. We could thus define the expectation of R as:

$$E[R_t(\mathbf{g}_t)] = \underbrace{\frac{1}{2}\sum_{i=1}^{n} d_{i,t}}_{\text{Edges}} - \underbrace{\frac{n}{2}\log n}_{\text{t(n)}}.$$

This is the ratio of number of links to delete to the total size of the insurance network at which the network would still be connected in expectation:

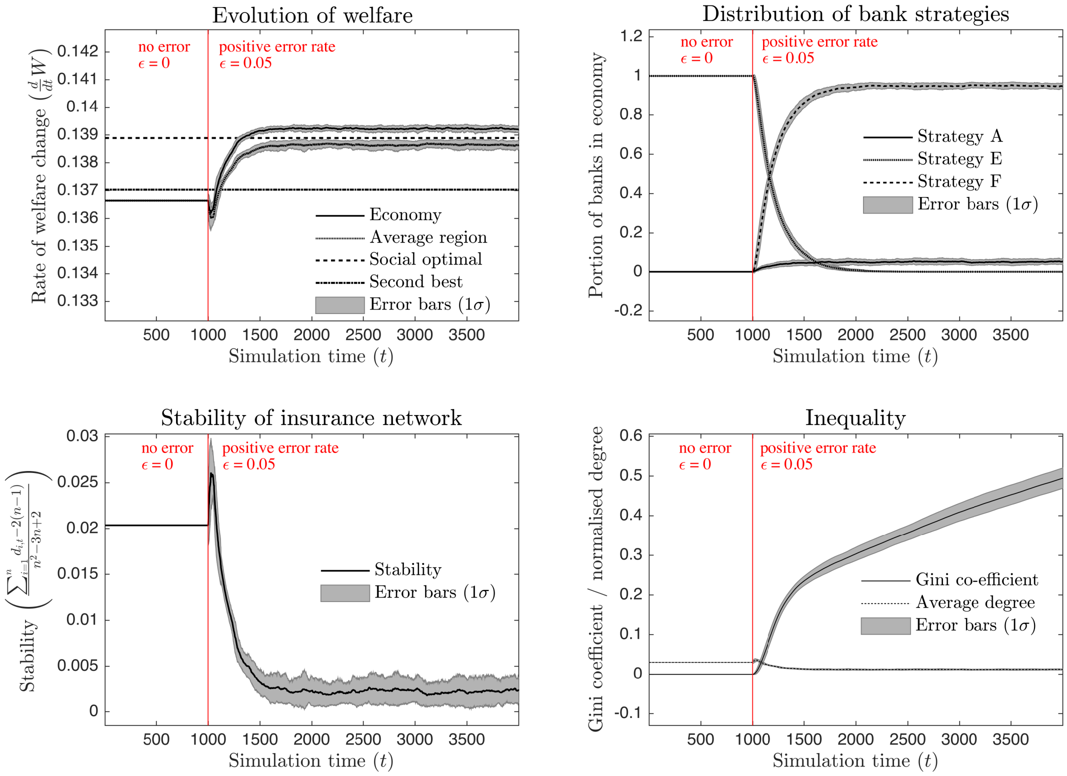
$$0 \leq \frac{2(E[R]-1)}{n(n-1-\log n)} \leq 1.$$

For the results in this chapter we relied solely on the more conservative measure of stability as introduced in the main text.

probability of $\epsilon = 0.05$ so that with a five percent chance banks choose a strategy at random rather than playing best-response (Blume, 1995; Young, 1998). The presence of random choice is equivalent to experimentation or the invasion of a new strategy. We can thus determine evolutionarily stable states (Foster and Young, 1990; Maynard Smith and Price, 1973; Maynard Smith and Parker, 1976). In discussing the simulation results in this and the next section it is further informative to distinguish between welfare of the economy as a whole and average welfare in each region. Because of growth in the economy, small differences in the value generated compound over time. For clarity of exposition and analysis we therefore study the rate of change of welfare rather than the absolute level of wealth in the economy.

We find that an economy just containing equilibrium banks forms is a steady state. As in the static equilibrium, no bank finds it beneficial to deviate from the equilibrium link formation probability. We thus find that both average and absolute welfare in the economy grow at a rate consistent with the second best (competitive) equilibrium as identified in the static model. Accordingly we find a relatively high degree of stability of the insurance network and no inequality.

However, once a small error rate is introduced and one bank plays the aggressive strategy, the best-response dynamics lead to a shift in equilibrium. We find a transition from a state with identical regions and only E-type banks to a hub and spoke system with one aggressive bank (A type) and otherwise free-riders (F type). Therefore, while the static equilibrium can persist in the dynamic game, it is neither evolutionarily nor stochastically stable. Interestingly, the aggregate growth of welfare of the economy, while close to the social optimal of the static model, is larger than what is expected from the social optimal of the static model. This effect is due to growth and leads to regions of different sizes. The region with the aggressive banks



Evolution of welfare

Distribution of bank strategies

Stability of insurance network

Inequality

Figure 4.3: Evolution of dynamic game

The figure shows simulation results for the dynamic game. The plots show means and one-standard-deviation error bars based on fifty runs and an economy with $n = 200$ *regions. The variables are as follows:* $\omega = 0.3$, $\bar{c} = 0$, $R = 1.2$, *and* $\rho = 0$, *which are chosen so that they fulfil the cheap insurance assumption of the model. The simulation starts with Equilibrium (E) banks only and no error rate in best-response* ($\epsilon = 0$)*. After* 1000 *time steps we introduce an error-rate in the best-response so that with a small probability* ($\epsilon = 0.05$) *agents play A rather than best-response.*

has higher costs for maintaining insurance links and thus grows at a lower rate. Over time the region with the aggressive bank will become comparatively small and the larger growth rate of the free-rider regions outweighs the slower growth in the one aggressive bank region. The effect of growing inequality is captured by the continuously increasing Gini co-efficient. In our model the aggressive bank performs a service to the insurance market that it is not compensated for. The average welfare growth is close to the social optimal as expected.

The resulting steady state with one central bank and otherwise free-riders has $n - 1$ insurance links. While this state is socially optimal and welfare-maximising it comes at the expense of lower stability of the insurance network and growing inequality. Nonetheless, we find that the dynamic formulation of the model leads to the socially optimal equilibrium. While the socially optimal equilibrium will always form, similarly to the static case the equilibrium is not unique, because any bank in the system could become the central A-type bank.

4.4 Effect of non-zero bailout probabilities

We have seen that in the dynamic version of the model the stable state consists of a core-periphery or hub and spoke system with one bank connected to all other banks in the system acting as a central intermediary in the insurance market. So far we have ignored any bank-specific factors that influence the insurance mechanism. It is well known that systemically important banks can be bailed out if they experience financial distress and we have shown in Chapters 2 and 3 that this influences interbank exposures. In our model we have shown that welfare in the economy is always larger for effective insurance. So, a social planner would prefer to bail out a bank if the costs from the bailout would not increase the gain in welfare, or

$\delta(d_i) < W_t(\theta = 1) - W_t(\theta = 0)$. Because insurance is cheap, in the sense of Assumption 4.2.2, a bailout, even of the entire banking system, is beneficial from a welfare perspective. We study an extension to the dynamic model that takes bailout probabilities into account. We assume that banks that are relatively more important to the insurance market have a higher probability of being bailed out if the insurance market is ineffective. For modelling purposes this probability is assumed as given ex-ante and we introduce it below. However, it should be noted that it is sufficient to think about the perception of consumers and other market-participants rather than a contractual bailout probability. We introduce the effect of non-zero bailout probabilities through bank-specific factors $\psi_{i,t}$ that change the profit-share ν^* that banks can retain.

The extent to which a bank benefits from non-zero bailout probabilities is captured by the premium term ρ. If ρ is equal to zero, no bank-specific factors exist and $\psi_{i,t} = 1$. Moreover, we want to capture two effects that influence whether a specific bank can retain a higher amount of profits ($\psi_{i,t} > 1$) as opposed to being penalised ($\psi_{i,t}$). The first is to model the relative importance of a bank compared to other banks. One could use a whole range of measures for such an importance. Because our model of the liquidity co-insurance market relies solely on connectedness and the stability of the insurance market is defined in terms of how many links need to be removed before the market becomes disconnected, the simplest possible way to capture systemic importance is to take the number of insurance links of a bank $d_{i,t}$ and compare it to the median number of insurance links $\bar{d}_t$. The second effect we would like to incorporate is that the relative importance of a bank only matters if the insurance market is relatively fragile. Therefore, the higher the stability of the insurance market in the sense of Eq. 4.41, the lower the premium that is placed on a bank that is relatively more important.

This expectation by consumers as a bank-specific scaling factor $0 \leq \psi_i$ in ν_i, where ψ_i is such that $\partial\psi/\partial R < 0$ and $\partial\psi/\partial d_i \geq 0$. However, the more stable the network, the smaller the effect of an individual bank's centrality on its ψ_i. The following function for bank-specific factors captures precisely these effects

$$\psi_{i,t} = (1-\rho) + 2\rho\left(1 - \frac{1}{1 + \left(d_{i,t-1}\bar{d}_{t-1}^{-1}\right)^{1-S_t}}\right). \tag{4.43}$$

with $\bar{d}_{t-1} = \frac{1}{n}\sum_{i=1}^{n} d_i$ is the average number of insurance links that banks maintain. ψ_i is defined if at least one insurance link exists. Because the stability of the network depends on the number of edges to remove, it is natural to use the number of insurance links of a bank (degree) relative to the average number of insurance links as a simple measure for its systemic importance. The exponent in the denominator of Eq. 4.43 is such that it is close to one for a fragile network in which only few links need to be removed before insurance becomes ineffective, but close to zero in a stable network. In a stable network therefore, banks do not benefit from a higher centrality, whereas in a fragile network they do.

We study the effect of introducing bank-specific factors through simulations initialised with a well-mixed population of banks and the largest possible premium for a bank equal to $\rho = 0.1$. After 2000 time periods we get rid of bank-specific factors by getting rid of the premium, or $\rho = 0$. Figure 4.4 shows the simulation results.

In the absence of bailout guarantees we would find a well-mixed distribution of bank strategies to converge to an insurance market with one central bank and the remaining banks being free-riders. However, if banks can increase their retained profits by maintaining a larger number of insurance links and thus becoming more important to the insurance network, we find that at least under some parameter

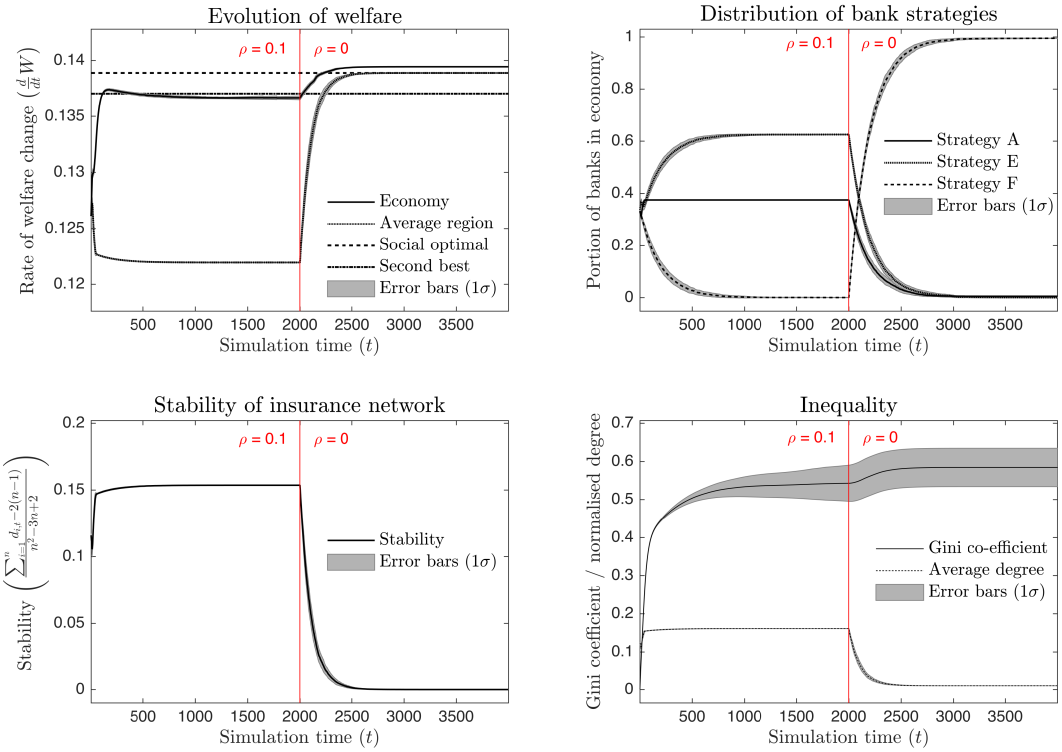


Figure 4.4: Evolution with positive bailout probability

The figure shows simulation results for the dynamic game. The plots show means and one-standard-deviation error bars based on fifty runs and an economy with $n = 200$ *regions. The variables are as follows:* $\omega = 0.3$, $\bar{c} = 0$, $R = 1.2$, *and* $\epsilon = 0$, *which are chosen so that they fulfil the cheap insurance assumption of the model. The simulation starts with a well-mixed population of A, E, and F banks and no error rate in best-response. Banks with higher degree benefit from implicit bailouts as modelled by* $\rho = 0.1$ *as long as the stability of the insurance market is low enough. After* 2000 *time steps we model a policy change so that* $\rho = 0$ *and no bank benefits from being more connected.*

configurations, the economy consists of only E type and A type banks. The larger average degree per bank leads to a higher stability of the insurance network. What is interesting is that despite the relatively larger number of links the welfare growth of the economy as a whole is close to the second best outcome of the static model. However, the average welfare growth per region is significantly below the second best benchmark.

In the absence of the premium $\rho = 0$ we find a dynamic reversion to the hub and spoke insurance network and the stable state at low stability, higher inequality, and levels of welfare growth close to the first best (both for the economy as a whole and the average per region). Thus, if there exist non-zero bailout probabilities that allow relatively more important banks to retain a larger profit share, this leads to a more stable insurance network at the cost of higher inequality and lower average welfare per region.

4.5 Conclusions

We have introduced a fairly general game of liquidity co-insurance that allows us to study the endogenous formation of interbank insurance links and resulting network properties. Contrary to many previous works (notably AG) we did not study liquidity co-insurance as an exchange of binding credit lines or interbank deposits but as an insurance contract contingent on the effectiveness of private insurance. Moreover, we combine liquidity co-insurance as a rationale to form financial links with alternative motivations of banks to act in the interbank market. We are able to achieve both by having introduced an insurance clearing mechanism that is non-static and allows liquidity to flow flexibly throughout the insurance network. While the insurance mechanism itself is iterative, we show in proposition 4.2.1 that in the absence of an aggregate liquidity shortfall any connected insurance network can absorb independent liquidity shocks. One could therefore derive the unique clearing vector directly based on the work by Eisenberg and Noe (2001). We must note as one limitation of the study that the insurance market clearing could take a long time. However, this does not strike us as a serious limitation in terms of modelling assumption. We study the stability of the insurance network as the inverse of the number of insurance links to remove before the insurance market becomes ineffective.

Our formulation of liquidity insurance is also consistent with empirical evidence for frequent renegotiation of interbank debt contracts (David and Lehar, 2014, 2015; Leitner, 2005) as well as the effect of pre-existing relationship on lending terms in times of distress (Cocco, Gomes and Martins, 2009). Modelling financial co-exposures as contracts with unknown exposure magnitude that moreover are state-contingent (in our case contingent on the effectiveness of the insurance network as a whole) seems innovative and may be useful for the analysis of the effect of network structures on systemic risk. To date there is no consensus on the question whether and how the structure of financial networks influences the spread of contagious events.[49] Most works in these areas find that whether or not the structure of the financial network matters depends on the magnitude and type of shock to the system. For instance, Acemoglu, Ozdaglar and Tahbaz-Salehi (2015) show that under their model assumptions the stability of the financial network is larger in more densely connected networks for small negative shocks, while for large shocks, more connected systems are less stable. Rather than taking the network structure as given and varying the nature of the shock, it may be more appropriate to think about financial exposures

---

[49] Amongst others compare the works by Acemoglu, Ozdaglar and Tahbaz-Salehi (2015), Battiston et al. (2012*b*,*a*), Elliott, Golub and Jackson (2014), Gai and Kapadia (2010); Gai, Haldane and Kapadia (2011), Glasserman and Young (2015), Haldane and May (2011), and Ladley (2013).

as state-dependent and thus vary the network structure as a consequence of a shock. Such an analysis would be consistent with findings that systemic risk is caused by the co-exposure of financial institutions to common assets (Allen, Babus and Carletti, 2012) rather than by direct exposure channels such as interbank lending. It would further be consistent with the finding that during the financial crisis of 2008 banks withdrew from the interbank market and liquidity became inaccessible rather than an overall liquidity shortfall having hit the economy (Afonso, Kovner and Schoar, 2011).

We show that given incomplete information and a one-off simultaneous move game, the static model results in a regular insurance network with a homogenous number of links per bank and a high degree of stability. We know from empirical evidence that interbank markets are tiered and have a core-periphery structure (Craig and von Peter, 2014) in which some few banks have a large number of links with most banks only holding a small number of links. The dynamic formulation of the model in which banks update their insurance links based on the observed distribution of strategies of other banks refines this result and leads to an extreme of an insurance market with one central hub that acts as an insurance mediator for the remainder of the market. Only when we introduce a comparative advantage for banks that hold more insurance links do we find a market structure made up of a tightly-knit core of aggressive banks, all of which are connected to each other, and a remaining set of banks with few connections amongst each other but with links to banks in the core. We model this comparative advantage as a premium from being systemically important, which allows more important banks to retain a larger profit share. Whether benefits from systemic importance are tangible, or are conferred through some sort of intangible status that reduces the participation constraint of depositors, is immaterial to the analysis. Thus, we provide an alternative explanation of core periphery structures in interbank markets, which arise endogenously when banks not only insure against liquidity shocks, but also benefit from non-zero bailout probabilities.

In our model we ignore intermediation between wealth and profitable investment opportunities as a possible explanation for core-periphery structures (cf. Farboodi, 2014). Farboodi discusses that bailout probabilities are not only a consequence of the network structure, but actually influence the network formation itself. With our extension of the dynamic version of the liquidity insurance formation game we provide a formal model of such a feedback mechanism.

Our model produces one inconsistency with empirical findings. Craig and von Peter (2014) show that banks in the core tend to be large. Banks in our model bear high costs to become systemically important and thus the regions in which they operate grow more slowly than adjacent regions. Therefore, the systemically important banks are more connected but in our model are smaller than less important banks. This effect is due to ignoring interest payments between banks altogether. Akram and Christophersen (2012) provide evidence that shows banks of systemic importance (in terms of size and connectedness) pay lower interest rates in overnight lending. If we were to introduce interest rates for claims made under liquidity co-insurance this inconsistency would vanish and costs for insurance would be shared more evenly. We further ignore idiosyncratic counter party risks in the current formulation of the model, which has been shown to influence refinancing costs (Zawadowski, 2013). Moreover, it has been shown that cooperative actions depend on reciprocity and trust (Bräuning and Fecht, 2012; Saavedra, Smith and Reed-Tsochas, 2010). Currently free-riders are not punished in any form. Introducing differential interest rates would allow such discrimination.

Recent advances in coordination games on graphs have studied the co-evolution of the action of players and the structure in which they are embedded (Galeotti et al., 2010; Bramoullé, Kranton and D'Amours, 2014). We introduce a function in which more central (in terms of degree centrality) banks have a competitive advantage. At the same time, this advantage diminishes the more stable the network becomes. Many recursive centrality measures such as eigenvector centrality (cf. Jackson, 2008 or Newman, 2010 for instance) not only increase in the degree of a bank (node) iteself, but also in the degree of its neighbours. Thus, if the centrality of a node determines the extent of the competitive advantage, then forming a larger number of insurance links is an action with local complements. However, with accumulating insurance links or in any homogenous financial network the payoffs from having such links would diminish. Currarini, Fumagalli and Panebianco (2013) discuss the role of negative externalities in a network context in which actions are local complements. While close to the work of Ballester, Calvó-Armengol and Zenou (2006) they introduce the notion that the extent of complementarity of actions decreases with the accumulation of actions. Thus, an interesting extension of our work would be to build on the work of Bramoullé, Kranton and D'Amours (2014) and formalise the effect of local coordination in the presence of local complements and global substitutes.

Chapter 5

Discussion and Implications

We begin by discussing our results in relationship to the literature on the role of a lender of last resort, and examine it with regards to implications for regulators and policy makers. We then discuss the need for further research into disentangling the roles of financial intermediation, liquidity co-insurance, and strategic behaviour in interbank markets. We follow with a discussion of limitations of the theoretical models proposed in this thesis, especially the absence of ex-ante heterogeneity in banks and the absence of social influence and imitation in the evolution of behaviour in our models of liquidity co-insurance. Lastly, we suggest that our theoretical results and modelling approach are an applied example of a novel class of coordination games in networks that is worthwhile exploring.

5.1 Policy implications

Our work has at least two implications for regulators. The empirical example of Germany shows that banks have very different incentives for acting in the interbank market. Credit cooperatives and savings banks are universal banks with a regional focus and are important to depositors as well as a source of funding for businesses.

These banks tend to rely heavily on the interbank market as a source of managing liquidity needs with little recourse to other sources of funding such as bond markets. Their lending and borrowing does not tend to impact their systemic importance as much. This finding is consistent with Arinaminpathy, Kapadia and May (2012) who find that the systemic importance of banks, or rather the potential for contagious effects, increases superlinearly with bank size and connectivity. The finding is also consistent with Craig and von Peter (2014) and Cajueiro and Tabak (2008) who show that size is the single most important predictor of being a core bank. Therefore, microprudential measures aimed at limiting systemic risk should be tailored to at least two types of banks, with less stringent requirements for smaller institutions with a regional focus.

To elaborate, in their study of short-term funding markets Anand, Gai and Marsili (2012) show that credit relations can only be rebuilt slowly and that transitioning from central liquidity provision back to private liquidity provision can be slow and inefficient. They consider contagion through a channel of reputation, in which the arrival of bad news about one bank leads to a loss of confidence, which under some conditions can lead to a collective loss of confidence and thus a liquidity crisis. Anand, Gai and Marsili suggest to mitigate rollover risk by increasing the resilience of banks through higher levels of capital, increasing transparency, and by relying on a central counter party. Increasing transparency and making available information relevant to the creditworthiness of financial institutions to other market participants could jeopardise trade secrets. Moreover, increasing capital requirements lowers the amount of loans these institutions can provide. Channeling all liquidity provision through a central counter party is possible, but would come at the cost of reducing peer monitoring incentives (Bräuning and Fecht, 2012; Diamond, 1984). Given that the potential of contagious effects of comparatively small institutions is limited, a different approach seems more suited. Anand, Gai and Marsili show that it is preferable to maintain private liquidity provision. Therefore, central banks, who often have access to detailed balance sheet information of banks including exposures between banks, could provide explicit guarantees to smaller banks during liquidity crises. Such guarantees should be valid for a limited amount of time and announced with a pre-defined end date in order to minimise moral hazard. This approach would eliminate bank-specific risk factors temporarily and thus should keep short-term funding markets intact even in the light of uncertainty about counter party risk.

The second type of bank that regulation must be adapted to is large private universal banks. Our empirical results show that private commercial banks rely less on the interbank market for liquidity provision, but that changes in interbank exposures influence a proxy measure for their systemic importance. The theoretical results in Chapter 3 suggest that the presence of uncertainty about the lender of last resort, or 'creative ambiguity' (Freixas, 1999), produces banks of different sizes and that the degree of uncertainty influences interest rate payments between banks. Large banks will borrow in the interbank market and invest in profitable investment opportunities. This result is consistent with the intermediation role of banks and channelling funds to profitable investment opportunities without precautionary hoarding (Acharya and Merrouche, 2012). Thus the presence of a lender of last resort, or the potential of bailouts, increases the loan provision to the private sector. The simulation results in Chapter 4 further suggest that the presence of bailout probabilities induces banks to form more links on average, which has positive consequences for the stability of the interbank market without sacrificing aggregate welfare. Such an incentive would disappear with the presence of a central counter party.

Therefore, for large private universal banks it seems appropriate to maintain ambiguity about bailouts while increasing the ability of absorbing liquidity shocks through higher levels of capital. Shapiro and Skeie (2015) discuss how the regulator can use this uncertainty to manage risk taking by banks. From our simulation results it seems that creating an incentive to become more connected that decreases in the overall stability of the financial system could be a viable option. This could be achieved by introducing a systemic risk tax as argued by Freixas and Rochet (2013) and Anand, Gai and Marsili (2012) for instance. This tax could be tied to a publicly reported measure of funding liquidity available in the interbank market. Such a tax could even be dependent on bank-specific measures of systemic importance as suggested by Thurner and Poledna (2013) or Battiston et al. (2012*c*). It would be a step towards considering monetary policy and prudential regulation in conjunction, which has been suggested by Freixas, Martin and Skeie (2011). In addition to that arguments have been made elsewhere for higher capital requirements for large banks in order to increase the ability of banks to absorb shocks or to scale down banks altogether (Mehran, Morrison and Shapiro, 2012).

Furthermore, in order to further the usefulness of the model in Chapter 4 for policy makers, it could be interesting to examine the rewiring of the liquidity co-insurance links when introducing aggregate liquidity shocks. This could be done through simulations and by introducing random removals of banks from the insurance system. Note that this is removal is quite different from bank default and thus a more realistic modelling assumption.

5.2 Intermediation, liquidity co-insurance, and strategic behaviour

We have shown that different drivers of the interbank market exist and that the presence of uncertain non-zero bailout probabilities can induce interbank lending. Furthermore, we have introduced a model that allows us to study the endogenous formation of financial networks in which both the liquidity management function as well as incentives of becoming systemically important are considered. So far we have not extended the model to include intermediation as a further driver of interbank lending (Diamond, 1984; Farboodi, 2014; Gale and Kariv, 2007). Future empirical work could focus on disentangling the relative importance of intermediation relative to strategic positioning and liquidity co-insurance.

Most models that study interbank markets as a mechanism to channel funds from liquidity providers to profitable investment opportunities assume that banks are endowed with access to investment opportunities with different returns. In order to establish causality between the drivers of interbank lending activities and financial exposures one would need detailed access to the potential loan portfolio of a bank in addition to detailed balance sheet information and exposures between banks. Such empirical work provides interesting and challenging future research opportunities.

Moreover, there is scope for extending the network formation model with ex-ante heterogeneity of banks, either in terms of size or in terms of returns to the productive technology. The appeal of not assuming heterogeneity ex-ante in any of the models in this thesis is to show that tiered and structured financial systems can evolve purely from the repeated interaction of market participants and in light of the assumed incentive structures. However, if one were to assume heterogeneity in returns to the profitable investment opportunity and allow banks to form trade relationships as in Farboodi (2014), one could derive predictions of typical network structures forming from the respective mechanisms. If one were to analyse the three different mechanisms as a structural model in varying overlapping configurations one ought to be able to formulate predictions that can be compared to observed financial networks. Thus, while direct causality may be harder to establish, this indirect way of comparing drivers of financial networks seems like a promising avenue of future research. Heterogeneity in bank sizes has further been shown to influence contagious effects (Iori and Jafarey, 2001), so it could be interesting to study a more elaborate measure of systemic risk in a model with heterogenous banks.

5.3 Social learning and bank-specific factors

It has been shown that relationships and bank-specific risk factors play an important role in lending and borrowing decisions of banks (Allen et al., 2012; Bräuning and Fecht, 2012; Cocco, Gomes and Martins, 2009; Heider, Hoerova and Holthausen, 2009; Zawadowski, 2013). In fact Acharya, Gromb and Yorulmazer (2012) argue that one role of a lender of last resort consists of counterbalancing a shift in market power during crises to banks with higher liquidity. To account for bank-specific factors the empirical work in Chapter 2 accounts for a range of balance sheet items in addition to dummy variables capturing bank and time effects. However, the models in Chapter 3 and 4 both ignore bank-specific factors beyond measures of systemic importance. It seems difficult to introduce such factors into a theoretical model of interbank markets without assuming some sort of ex-ante differences between banks. Thus, further extensions to this work, similar to the one suggested above for the effect of financial intermediation, could consider heterogeneity of banks with regards to some measure of counter party risk or presence of good lending relationships.

Building on the mechanism design literature, Archetti et al. (2011) argue that expected levels of cooperation are higher when screening is possible before the interaction between two agents. Due to the complexity of financial co-exposures it seems that assuming some sort of objective risk measure is a demanding modelling assumption. One could introduce heterogeneity through simple observable measures such as endowed capital, size, or leverage. It could further be interesting to study a model that considers otherwise homogeneous banks which possess some sort of score for social status. There is evidence that social status signals quality when obtaining an objective quality measure is impossible (Podolny, 1993, 2005) and that social proximity play a role in the formation of risk-sharing networks (Fafchamps and Gubert, 2007). The same argument has been made for trust-based partner choice in networks, where agents are in control of their links (Zhong et al., 2011). There is evidence that the interaction between reputation, trust, and imitation influences the stability of cooperation between agents facing social dilemmas (Saavedra, Smith and Reed-Tsochas, 2010).

A further extension to the dynamic network formation model in Chapter 4 consists of introducing social learning in addition to (stochastic) best-response dynamics. It is well known that individual decision-making is influenced by institutions and conventions and that imitation and herding behaviour can drive decisions (Bikhchandani, Hirshleifer and Welch, 1992, 1998; Granovetter, 1985; Young, 1993*a*). Macy (1991) argues from a sociological perspective that learning and adaptive behaviour in experimental iterated prisoner's dilemmas decisively influence equilibrium selection.[50] A range of papers have shown empirically that behaviour and information

---

[50] Also see Macy (2002) on learning dynamics in social dilemmas.

spread in networks: free-riding in social dilemmas (López-Pintado, 2008), knowledge in collaboration networks (Singh, 2005), and health behaviour in friendship networks (Christakis and Fowler, 2012*a*; Fowler and Christakis, 2008; Christakis and Fowler, 2012*b*). In an ongoing research effort, a range of models study how social structure influences the aggregation of information (Acemoglu, Bimpikis and Ozdaglar, 2014; Acemoglu, Ozdaglar and ParandehGheibi, 2010; Acemoglu and Jackson, 2015; Blume et al., 2011; Kozma and Barrat, 2008; Golub and Jackson, 2010). They all show that when influential agents or groups of agents exist in a population, or the updating of beliefs is not balanced, social learning can lead to distorted beliefs. Onnela and Reed-Tsochas (2010) show through an empirical analysis of technology adoption behaviour in an online context that social influence (i.e. contagious spreading) becomes a dominant force of adoption after a threshold of adopters is reached.

It is unclear exactly how network structures influence behaviour adoption processes. Jackson and Yariv (2007) propose a framework that relates a so-called diffusion equilibrium to network and payoff properties. Young (2011) provides a model suggesting that social structure matters for the global diffusion of social innovations, and particularly that sparse network structures support diffusion. Opposing arguments exist regarding the kind of structure that supports diffusion of behaviour (see Centola, 2010). When learning depends on social affirmation, theoretical models suggest that long ties halt the diffusion process (Centola and Macy, 2007).

A natural way to extend the model in Chapter 4 in a way that considers social influences in learning is to introduce uncertainty about the link formation strategies pursued by banks. In the current formulation of the model the information set of banks contains the distribution of strategies across the entire economy. One could study a model in which the overall structure of the liquidity co-insurance network is unknown to banks and banks only know their own strategy, that of banks to whom they are linked, and know an overall score for the stability of the financial network. It would be interesting to see whether inefficient states of private liquidity co-insurance would arise or whether insurance would even collapse.

5.4 Rethinking nominal co-exposures and a new class of coordination games in networks

Much of the research into the role of network structures in systemic risk takes financial exposures as given. Therefore, the underlying assumption of the majority of work on systemic risk is that exposures in principle are measurable quantities. The liquidity co-insurance mechanism introduced in Chapter 4 breaks with this tradition in two central ways. It considers insurance as a binary contract that gives the right to draw an arbitrary amount of liquidity. Moreover, this commitment to provide liquidity is only binding when no aggregate liquidity shortfall exists and liquidity can be redistributed in the financial system, or in the words of Chapter 4, the private provision of liquidity co-insurance is effective.

While this assumption may be strong when thinking of interbank lending or interbank deposit contracts, a large proportion of interbank co-exposures exists through indirect channels such as exposure to common assets (Caccioli et al., 2014; Allen, Babus and Carletti, 2012). It has been shown that because of mark-to-market accounting rules small changes in asset values can lead to deleveragings and liquidity crises (Acharya and Viswanathan, 2011; Adrian and Shin, 2010). Brunnermeier (2009) further explains that the collapse of liquidity markets during the global financial crisis in 2007-2008 was due to a widespread lack of trust in the creditworthiness of financial institutions caused by uncertainty regarding the exposures to distressed assets. If exact co-exposures are unknown, defaulting to binary exposures of uncertain magnitude is probably not the best assumption possible for research on systemic risk even though it seems like a plausible one. More importantly, it seems worthwhile exploring state-dependent financial co-exposures in more detail.

Especially in theoretical work on systemic risk many results exist that identify tipping points for connectedness or shocks under which contagious defaults occur (cf. Chapter 1). An interesting area of further research could examine how such results are affected if bilateral exposures not only depend on risk factors of the counter parties, but also on the structure of the financial network overall. This is an area of research which could be interesting to scholars studying systemic risk, liquidity co-insurance, or financial network formation. Separate from its context in finance, such a research programme could also be interesting to scholars studying coordination in network games. Building on the work of Belhaj, Bramoullé and Deroian (2014), Bramoullé and Kranton (2007), and Galeotti et al. (2010) one could imagine a model in which agents are embedded in a dynamically evolving network in which they only have local information, i.e. they know their own actions and those of their neighbours. Agents choose to exert an effort which consists of forming links and maintaining links. Depending on the network position of an agent or its number of links each agent derives a payoff. This payoff would vary with local actions when they are either complements or substitutes. In this sense the model would be close to Belhaj, Bramoullé and Deroian. In addition to local interaction and coordination the payoff from the effort would also vary in the global network structure.

The extension of the dynamic link formation network with the presence of non-zero bailout probabilities in Chapter 4 seems to be an applied version of such a model.

It would be interesting to formulate a general version of it and see whether analytical results can be obtained.

References

Abadie, Alberto. 2005. "Semiparametric difference-in-differences estimators." *The Review of Economic Studies*, 72: 1–19.

Abreu, Dilip, and Markus K Brunnermeier. 2003. "Bubbles and Crashes." *Econometrica*, 71(1): 173–204.

Acemoglu, Daron, and Matthew O Jackson. 2015. "History, expectations, and leadership in the evolution of social norms ." *The Review of Economic Studies*, 82(2): 423–456.

Acemoglu, Daron, Asuman Ozdaglar, and Ali ParandehGheibi. 2010. "Spread of (mis)information in social networks." *Games and Economic Behavior*, 70(2): 194–227.

Acemoglu, Daron, Asuman Ozdaglar, and Alireza Tahbaz-Salehi. 2013. *Systemic Risk and Stability in Financial Networks.* NBER Working Paper No. 18727, available at: http://www.nber.org/papers/w18727 [Accessed: 11 November 2014].

Acemoglu, Daron, Asuman Ozdaglar, and Alireza Tahbaz-Salehi. 2015. "Systemic Risk and Stability in Financial Networks." *The American Economic Review*, 105(2): 564–608.

Acemoglu, Daron, Kostas Bimpikis, and Asuman Ozdaglar. 2014. "Dynamics of information exchange in endogenous social networks." *Theoretical Economics*, 9(1): 41–97.

Acharya, Viral V. 2009. "A theory of systemic risk and design of prudential bank regulation." *Journal of Financial Stability*, 5(3): 224–255.

Acharya, Viral V, and David Skeie. 2011. "A model of liquidity hoarding and term premia in inter-bank markets." *Journal of Monetary Economics*, 58(5): 436–447.

Acharya, Viral V, and Ouarda Merrouche. 2012. "Precautionary hoarding of liquidity and interbank markets: evidence from the subprime crisis." *Review of Finance*, 17(1): 107–160.

Acharya, Viral V, and Siva Viswanathan. 2011. "Leverage, Moral Hazard, and Liquidity." *The Journal of Finance*, 66(1): 99–138.

Acharya, Viral V, and Tanju Yorulmazer. 2007. "Too many to fail—An analysis of time-inconsistency in bank closure policies." *Journal of Financial Intermediation*, 16(1): 1–31.

Acharya, Viral V, Denis Gromb, and Tanju Yorulmazer. 2012. "Imperfect Competition in the Interbank Market for Liquidity as a Rationale for Central Banking." *American Economic Journal: Macroeconomics*, 4(2): 184–217.

Acharya, Viral V, Deniz Anginer, and A Joseph Warburton. 2015. *The End of Market Discipline? Investor Expectations of Implicit State Guarantees.* Working Paper, available at: http://www.ssrn.com/abstract=1961656 [Accessed: 5 May 2016].

Acharya, Viral V, Douglas Gale, and Tanju Yorulmazer. 2011. "Rollover risk and market freezes." *The Journal of Finance*, 66(4): 1177–1209.

Adrian, Tobias, and Hyun Song Shin. 2010. "Liquidity and leverage." *Journal of Financial Intermediation*, 19(3): 418–437.

Afonso, Gara, Anna Kovner, and Antoinette Schoar. 2011. "Stressed, Not Frozen: The Federal Funds Market in the Financial Crisis." *The Journal of Finance*, 66(4): 1109–1139.

Afonso, Gara, Anna Kovner, and Antoinette Schoar. 2013. *Trading Partners in the Interbank Lending Market.* Federal Reserve Bank of New York Staff Reports, No. 620, available at: http://www.newyorkfed.org/research/staff_reports/sr620.html [Accessed: 12 June 2013].

Akram, Q Farooq, and Casper Christophersen. 2012. *Investigating gains from systemic importance in a small interbank market.* Working Paper, available at: http://www.eea-esem.com/files/papers/eea-esem/2012/2770/AkramChristophersen_2012.pdf [Accessed: 11 November 2014].

Allen, Franklin. 2001. "Do Financial Institutions Matter?" *The Journal of Finance*, 56(4): 1165–1175.

Allen, Franklin, Ana Babus, and Elena Carletti. 2012. "Asset commonality, debt maturity and systemic risk." *Journal of Financial Economics*, 104(3): 519–534.

Allen, Franklin, and Douglas Gale. 1998. "Optimal Financial Crises." *The Journal of Finance*, 53(4): 1245–1284.

Allen, Franklin, and Douglas Gale. 2000. "Financial Contagion." *The Journal of Political Economy*, 108(1): 1–33.

Allen, Jason, James Chapman, Federico Echenique, and Matthew Shum. 2012. *Efficiency and Bargaining Power in the Interbank Loan Market.* Bank of Canada Staff Working Papers, No. 2012-29, available at: http://www.bankofcanada.ca/2012/09/working-paper-2012-29/ [Accessed: 18 December 2015].

Anand, Kartik, Prasanna Gai, and Matteo Marsili. 2012. "Rollover risk, network structure and systemic financial crises." *Journal of Financial Economics*, 36(8): 1088–1100.

Anand, Kartik, Prasanna Gai, Sujit Kapadia, Simon Brennan, and Matthew Willison. 2013. "A network model of financial system resilience." *Journal of Economic Behavior and Organization*, 85: 219–235.

Angelini, Paolo, Andrea Nobili, and Cristina Picillo. 2011. “The Interbank Market after August 2007: What Has Changed, and Why?” *Academy of Management Review*, 43(5): 923–958.

Archetti, Marco, Francisco Úbeda, Drew Fudenberg, Jerry Green, Naomi E Pierce, and Douglas W Yu. 2011. “Let the Right One In: A Microeconomic Approach to Partner Choice in Mutualisms.” *The American Naturalist*, 177(1): 75–85.

Arinaminpathy, Nimalan, Sujit Kapadia, and Robert M May. 2012. “Size and complexity in model financial systems.” *Proceedings of the National Academy of Science*, 109(45): 18338–18343.

Ashcraft, Adam, James McAndrews, and David Skeie. 2011. “Precautionary reserves and the interbank market.” *Journal of Money, Credit and Banking*, 43(2): 311–348.

Ashenfelter, Orley, and David Card. 1985. “Using the Longitudinal Structure of Earnings to Estimate the Effect of Training Programs.” *The Review of Economics and Statistics*, 67(4): 648–14.

Axelrod, Robert. 1981. “The emergence of cooperation among egoists.” *The American Political Science Review*, 75: 306–318.

Axelrod, Robert. 1984. *The Evolution of Co-operation.* New York: Penguin Books.

Axelrod, Robert, and D Dion. 1988. “The Further Evolution of Cooperation.” *Science*, 242: 1385–1390.

Axelrod, Robert, and William D. Hamilton. 1981. “The Evolution of Cooperation.” *Science*, 211: 1390–1396.

Babus, Ana. 2011. *Endogenous Intermediation in Over-the-Counter Markets.* Working Paper, available at http://www.anababus.net/research/otc.pdf [Accessed: 11 November 2014].

Babus, Ana. 2014. *The Formation of Financial Networks.* Working Paper, available at: http://www.anababus.net/research/formnet.pdf [Accessed: 11 November 2014].

Bala, Venkatesh, and Sanjeev Goyal. 2000. “A Noncooperative Model of Network Formation.” *Econometrica*, 68(5): 1181–1229.

Ballester, Coralio, Antoni Calvó-Armengol, and Yves Zenou. 2006. “Who's Who in Networks. Wanted: The Key Player.” *Econometrica*, 74(5): 1403–1417.

Bankenverband. 2015. *Einlagensicherung der privaten Banken.* Booklet, available at: https://bankenverband.de/service/einlagensicherung/ [Accessed: 7 October 2015].

Bartram, Söhnke M, Gregory W Brown, and John E Hund. 2007. “Estimating systemic risk in the international financial system.” *Journal of Financial Economics*, 86(3): 835–869.

Battiston, Stefano, Domenico Delli Gatti, Mauro Gallegati, Bruce Greenwald, and Joseph E Stiglitz. 2012*a*. "Default cascades: When does risk diversification increase stability?" *Journal of Financial Stability*, 8(3): 138–149.

Battiston, Stefano, Domenico Delli Gatti, Mauro Gallegati, Bruce Greenwald, and Joseph E Stiglitz. 2012*b*. "Liaisons dangereuses: Increasing connectivity, risk sharing, and systemic risk." *Journal of Economic Dynamics and Control*, 36(8): 1121–1141.

Battiston, Stefano, Michelangelo Puliga, Rahul Kaushik, Paolo Tasca, and Guido Caldarelli. 2012*c*. "DebtRank: Too Central to Fail? Financial Networks, the FED and Systemic Risk." *Scientific Reports*, 2(541): 1–6.

Belhaj, Mohamed, Yann Bramoullé, and Frederic Deroian. 2014. "Network games under strategic complementarities." *Games and Economic Behavior*, 88: 310–319.

Bendor, Jonathan. 1993. "Uncertainty and the Evolution of Cooperation." *Journal of Conflict Resolution*, 37(4): 709–734.

Bendor, Jonathan, and Piotr Swistak. 1997. "The Evolutionary Stability of Cooperation." *The American Political Science Review*, 91(2): 290–307.

Bendor, Jonathan, Roderick Kramer, and Piotr Swistak. 1996. "Cooperation Under Uncertainty: What is New, What is True, and What is Important." *American Sociological Review*, 61(2): 333–338.

Bhattacharya, Sudipto, and Douglas Gale. 1987. "Preference Shocks, Liquidity, and Central Bank Policy." In *New Approaches to Monetary Economics*, edited by W Barnett and K Singleton. New York: Cambridge University Press.

Bhattacharya, Sudipto, and Kjell G Nyborg. 2013. "Bank bailout menus." *Review of Corporate Finance Studies*, 2(1): 29–61.

Bhattacharya, Sudipto, and Paolo Fulghieri. 1994. "Uncertain liquidity and interbank contracting." *Economics Letters*, 44(3): 287–294.

Bikhchandani, Sushil, David Hirshleifer, and Ivo Welch. 1992. "A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades." *Journal of Political Economy*, 100(5): 992–1026.

Bikhchandani, Sushil, David Hirshleifer, and Ivo Welch. 1998. "Learning from the Behavior of Others: Conformity, Fads, and Informational Cascades." *The Journal of Economic Perspectives*, 12(3): 151–170.

Binmore, Kenneth. 1998. *Game Theory and The Social Contract Volume 2: Just Playing.* Cambridge, MA: MIT Press.

Binmore, Kenneth, and Larry Samuelson. 1994. "An Economist's Perspective on the Evolution of Norms." *Journal of Institutional and Theoretical Economics*, 150: 45–45.

Bisias, Dimitrios, Mark Flood, Andrew W Lo, and Stavros Valavanis. 2012. *A Survey of Systemic Risk Analytics.* Office of Financial Research Working Paper, No. 0001, avilable at: http://bigdata.csail.mit.edu/sites/bigdata/files/sites/Lo%20abstract%20and%20paper%20-%20Systemic_OFR1_final.pdf [Accessed: 10 July 2013].

Bluhm, Marcel, Co-Pierre Georg, and Jan-Pieter Krahnen. 2016. *Interbank Intermediation.* Deutsche Bundesbank (2016), mimeo.

Blume, Larry, David Easley, Jon Kleinberg, Robert Kleinberg, and Éva Tardos. 2011. "Which Networks Are Least Susceptible to Cascading Failures?" *Foundations of Computer Science (FOCS), 2011 IEEE 52nd Annual Symposium*, 393–402.

Blume, Lawrence, David Easley, Jon Kleinberg, Robert Kleinberg, and Éva Tardos. 2013. "Network formation in the presence of contagious risk." *ACM Transactions on Economics and Computation*, 1(2): 6.

Blume, Lawrence E. 1995. "The Statistical Mechanics of Best-Response Strategy Revision." *Games and Economic Behavior*, 11: 111–145.

Bollobás, Béla. 2001. *Random Graphs. Cambridge studies in advanced mathematics*, Cambridge et al: Cambrdige University Press.

Bolton, Patrick, Tano Santos, and José A Scheinkman. 2011. "Outside and Inside Liquidity." *The Quarterly Journal of Economics*, 126(1): 259–321.

Boncinelli, Leonardo, and Paolo Pin. 2012. "Stochastic stability in best shot network games." *Games and Economic Behavior*, 75(2): 538–554.

Boss, Michael, Helmut Elsinger, Martin Summer, and Stefan Thurner. 2004. "Network topology of the interbank market." *Quantitative Finance*, 4(6): 677–684.

Bowles, Samuel, and Herbert Gintis. 2008. "Cooperation." In *The New Palgrave Dictionary of Economics*, edited by Steven N Durlauf and Lawrence E Blume, 228–234. Basingstoke: Nature Publishing Group.

Boyd, Robert, and Jeffrey P Lorberbaum. 1987. "No pure strategy is evolutionarily stable in the repeated Prisoner's Dilemma game." *Nature*, 327: 58–59.

Boyd, Robert, and Peter J. Richerson. 1988. "The evolution of reciprocity in sizable groups." *Journal of Theoretical Biology*, 132(3): 337–356.

Boyd, Robert, Herbert Gintins, and Samuel Bowles. 2010. "Coordinated Punishment of Defectors Sustains Cooperation and Can Proliferate When Rare." *Science*, 328: 617–620.

Bramoullé, Yann, and Rachel Kranton. 2007. "Public goods in networks." *Journal of Economic Theory*, 135(1): 478–494.

Bramoullé, Yann, Dunia López-Pintado, Sanjeev Goyal, and Fernando Vega-Redondo. 2004. "Network formation and anti-coordination games." *International Journal of Game Theory*, 33(1): 1–19.

Bramoullé, Yann, Rachel Kranton, and Martin D'Amours. 2014. "Strategic Interaction and Networks." *The American Economic Review*, 104(3): 898–930.

Bräuning, Falk, and Falko Fecht. 2012. *Relationship Lending and Peer Monitoring: Evidence from Interbank Payment Data.* Deutsche Bundesbank Discusion Paper, No. 22/2012, available at: http://www.bundesbank.de/Redaktion/EN/Downloads/Publications/Discussion_Paper_1/2012/2012_09_07_dkp_22.pdf?__blob=publicationFile [Accessed: 1 August 2013].

Brintrup, A, T Kito, E López, S New, and Felix Reed-Tsochas. 2011. *The structure of the Toyota supply network: The emergence of resilience.* CABDyN Working Paper, # 2011-05-012, available at: http://www.cabdyn.ox.ac.uk/complexity_PDFs/Working%20Papers%202011/WorkingPaper_ToyotaRobustness.pdf [Accessed: 11 May 2015].

Brunnermeier, Markus K. 2009. "Deciphering the Liquidity and Credit Crunch 2007-2008." *The Journal of Economic Perspectives*, 23(1): 77–100.

Brunnermeier, Markus K, and Lasse Heje Pedersen. 2005. "Predatory Trading." *The Journal of Finance*, 60(4): 1825–1863.

Brunnermeier, Markus K, and Martin Oehmke. 2013. "Bubbles, financial crises, and systemic risk." In *Handbook of the Economics of Finance*, edited by George M Constantinides, Milton Harris and Rene M Stulz, 1221–1288. Amsterdam: Elsevier.

Brusco, Sandro, and Fabio Castiglionesi. 2007. "Liquidity Coinsurance, Moral Hazard, and Financial Contagion." *The Journal of Finance*, 62(5): 2275–2302.

Cabrales, Antonio, Antoni Calvó-Armengol, and Yves Zenou. 2011. "Social interactions and spillovers." *Games and Economic Behavior*, 72(2): 339–360.

Cabrales, Antonio, Piero Gottardi, and Fernando Vega-Redondo. 2014. *Risk-Sharing and Contagion in Networks.* CESIFO Working Paper, No 4715, available at: http://ssrn.com/abstract=2425558 [Accessed: 11 November 2014].

Caccioli, Fabio, Munik Shrestha, Christopher Moore, and J Doyne Farmer. 2014. "Stability analysis of financial contagion due to overlapping portfolios." *Journal of Banking & Finance*, 46: 233–245.

Cajueiro, Daniel O, and Benjamin M Tabak. 2008. "The role of banks in the Brazilian interbank market: Does bank type matter?" *Physica A: Statistical Mechanics and its Applications*, 387(27): 6825–6836.

Card, David, and Alan B Krueger. 1994. "Minimum wages and employment: A case study of the fast food industry in New Jersey and Pennsylvania." *The American Economic Review*, 84(4): 772–793.

Carmen, Reinhart, and Kenneth Rogoff. 2014. "This Time Is Different: A Panoramic View of Eight Centuries of Financial Crises." *Annals of Economics and Finance*, 15(2): 1065–1188.

Castiglionesi, Fabio, and Noemi Navarro. 2011. *Fragile Financial Networks.* Working Paper, available at: https://dl.dropboxusercontent.com/u/39319144/NTW.pdf [Accessed: 11 November 2014].

Castiglionesi, Fabio, and Wolf Wagner. 2013. "On the efficiency of bilateral interbank insurance." *Journal of Financial Intermediation*, 22(2): 177–200.

Castiglionesi, Fabio, Fabio Feriozzi, Lóránth Gyängyi, and Loriana Pelizzon. 2014. “Liquidity coinsurance and bank capital.” *Journal of Money, Credit and Banking*, 46(2-3): 409–443.

Centola, Damon. 2010. “The Spread of Behavior in an Online Social Network Experiment.” *Science*, 329: 1194–1197.

Centola, Damon, and Michael W Macy. 2007. “Complex Contagions and the Weakness of Long Ties.” *American Journal of Sociology*, 113(3): 702–734.

Christakis, Nicholas A., and James H. Fowler. 2012*a*. “The Collective Dynamics of Smoking in a Large Social Network.” *The New England Journal of Medicine*, 358(21): 2249–2258.

Christakis, Nicholas A., and James H. Fowler. 2012*b*. “The Spread of Obesity in a Large Social Network over 32 Years.” *The New England Journal of Medicine*, 357(4): 370–379.

Cifuentes, Rodrigo, Gianluigi Ferrucci, and Hyun Song Shin. 2005. “Liquidity Risk and Contagion.” *Journal of the European Economic Association*, 3(2-3): 556–566.

Cocco, João F, Francisco J Gomes, and Nuno C Martins. 2009. “Lending relationships in the interbank market.” *Journal of Financial Intermediation*, 18(1): 24–48.

Cohen-Cole, Ethan, Eleonora Patacchini, and Yves Zenou. 2010. *Systemic risk and network formation in the interbank market.* CAREFIN Research Paper, available at: http://www.ne.su.se/polopoly_fs/1.221633.1422360775!/menu/standard/file/Cohen_Patacchini_Zenou_22.pdf [Accessed: 18 July 2014].

Cohen-Cole, Ethan, Eleonora Patacchini, and Yves Zenou. 2015. “Static and dynamic networks in interbank markets.” *Network Science*, 3(1): 98–123.

Cont, Rama, Amal Moussa, and Edson Bastos e Santos. 2013. “Network Structure and Systemic Risk in Banking Systems.” In *Handbook of Systemic Risk*, edited by Jean-Pierre Fouque and Joseph Langsam, 327–368. Cambridge: Cambridge University Press.

Cordella, Tito, and Eduardo Levy Yeyati. 2003. “Bank bailouts: moral hazard vs. value effect.” *Journal of Financial Intermediation*, 12(4): 300–330.

Craig, Ben, and Goetz von Peter. 2014. “Interbank tiering and money center banks.” *Journal of Financial Intermediation*, 23(3): 322–347.

Currarini, Sergio, Elena Fumagalli, and Fabrizio Panebianco. 2013. *Games on Networks: Direct Complements and Indirect Substitutes.* Working Paper, available at: http://services.bepress.com/feem/paper755/ [Accessed: 22 September 2014].

Dal Bó, Pedro, and Guillaume R Fréchette. 2011. “The Evolution of Cooperation in Infinitely Repeated Games: Experimental Evidence.” *The American Economic Review*, 101(1): 411–429.

David, Alexander, and Alfred Lehar. 2014. *Why are Banks Highly Interconnected?* Working Paper, available at: http://ssrn.com/abstract=1108870 [Accessed: 17 June 2014].

David, Alexander, and Alfred Lehar. 2015. *Imperfect Renegotiation in Interbank Financial Networks.* Working Paper, available at: http://ssrn.com/abstract=1108870 [Accessed: 4 November 2015].

Davies, Richard, and Belinda Tracey. 2014. "Too Big to Be Efficient? The Impact of Implicit Subsidies on Estimates of Scale Economies for Banks." *Journal of Money, Credit and Banking*, 46(1): 219–253.

Degryse, Hans, and Gregory Nguyen. 2007. "Interbank exposures: An empirical examination of contagion risk in the Belgian banking system." *International Journal of Central Banking*, 3(2): 123–171.

Demsetz, Rebecca S, Marc R Saidenberg, and Philip E Strahan. 1996. "Banks with Something to Lose: The Disciplinary Role of Franchise Value." *data.newyorkfed.org*, October: 1–14.

Diamond, Douglas W. 1984. "Financial Intermediation and Delegated Monitoring." *The Review of Economic Studies*, 51(3): 393–414.

Diamond, Douglas W, and Philip Dybvig. 1983. "Bank Runs, Deposit Insurance, and Liquidity." *The Journal of Political Economy*, 91(3): 401–419.

Diamond, Douglas W, and Raghuram G Rajan. 2005. "Liquidity Shortages and Banking Crises." *The Journal of Finance*, 60(2): 615–647.

Diamond, Douglas W, and Raghuram G Rajan. 2011. "Fear of Fire Sales, Illiquidity Seeking, and Credit Freezes." *Quarterly Journal of Economics*, 126(2): 557–591.

Di Maggio, Marco, and Alireza Tahbaz-Salehi. 2014. *Financial Intermediation Networks.* Columbia Business School Research Paper, available at: http://www.ssrn.com/abstract=2492007 [Accessed: 17 January 2015].

Duchin, Ran, and Denis Sosyura. 2014. "Safer ratios, riskier portfolios: Banks response to government aid." *Journal of Financial Economics*, 113(1): 1–28.

Dutta, Bhaskar, and Suresh Mutuswami. 1997. "Stable Networks." *Journal of Economic Theory*, 76(2): 322–344.

Economides, Nicholas. 1996. "The economics of networks." *International Journal of Industrial Organization*, 14(6): 673–699.

Eisenberg, Larry, and Thomas H Noe. 2001. "Systemic Risk in Financial Systems." *Management Science*, 47(2): 236–249.

Eisert, Tim, and Christian Eufinger. 2013. *Interbank Network and Bank Bailouts: Insurance Mechanism for Non-Insured Creditors?* Working Paper, available at: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1976383 [Accessed: 1 August 2013].

Elliott, Matthew, Benjamin Golub, and Matthew O Jackson. 2014. “Financial Networks and Contagion.” *The American Economic Review*, 104(10): 3115–3153.

Ellison, Glenn. 1993. “Learning, Local Interaction, and Coordination.” *Econometrica*, 61(5): 1047–1071.

Erdös, P, and A Rényi. 1959. “On Random Graphs.” *Publicationes Mathematicae (Debrecen)*, 6: 290–297.

Erdös, P, and A Rényi. 1960. “On the evolution of random graphs.” *Publication of the Mathematical Institute of the Hungarian Academy of Sciences*, 5: 17–61.

Erdös, P, and A Rényi. 1961. “On the Strength of Connectedness of a Random Graph.” *Acta Mathematica Academy of Sciences of Hungaria*, 12: 261–267.

Erol, Selman, and Rakesh Vohra. 2014. *Network Formation and Systemic Risk.* PIER Working Paper, No. 14-029, available at: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2500846 [Accessed: 11 November 2014].

Fafchamps, Marcel, and Flore Gubert. 2007. “The formation of risk sharing networks.” *Journal of Development Economics*, 83(2): 326–350.

Farboodi, Maryam. 2014. *Intermediation and Voluntary Exposure to Counterparty Risk.* Working Paper, available at: http://www.mfmgroup.org/documents/MaryamFarboodiJMP.pdf [Accessed: 11 September 2014].

Farhi, Emmanuel, and Jean Tirole. 2012. “Collective Moral Hazard, Maturity Mismatch, and Systemic Bailouts.” *The American Economic Review*, 102(1): 60–93.

Fehr, Ernst, and Urs Fischbacher. 2003. “The nature of human altruism.” *Nature*, 425: 785–791.

Fischbacher, Urs, Simon Gächter, and Ernst Fehr. 2001. “Are people conditionally cooperative? Evidence from a public goods experiment.” *Economics Letters*, 71(3): 397–404.

Fischer, Markus, Christa Hainz, JJrg Rocholl, and Sascha Steffen. 2014. *Government Guarantees and Bank Risk Taking Incentives.* Working Paper, available at: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2394607 [Accessed: 4 May 2016].

Foster, Dean, and H Peyton Young. 1990. “Stochastic evolutionary game dynamics.” *Theoretical population biology*, 38(2): 219–232.

Fowler, James H., and Nicholas A. Christakis. 2008. “Dynamic spread of happiness in a large social network: longitudinal analysis over 20 years in the Framingham Heart Study.” *British Medical Journal*, 338(7685).

Freixas, Xavier. 1999. *Optimal Bail Out Policy, Conditionality and Constructive Ambiguity.* SSRN Working Paper No. 400, available at: http://ssrn.com/abstract=199054 [Accessed: 13 January 2013].

Freixas, Xavier, and Bruno Parigi. 1998. "Contagion and Efficiency in Gross and Net Interbank Payment Systems." *Journal of Financial Intermediation*, 7(1): 3–31.

Freixas, Xavier, and Cornelia Holthausen. 2005. "Interbank market integration under asymmetric information." *Review of Financial Studies*, 18(2): 459–490.

Freixas, Xavier, and Jean-Charles Rochet. 2008. *Microeconomics of Banking.* 2nd ed., Cambridge, MA, London: The MIT Press.

Freixas, Xavier, and Jean-Charles Rochet. 2013. "Taming Systemically Important Financial Institutions." *Journal of Money, Credit and Banking*, 45(1): 37–58.

Freixas, Xavier, Antoine Martin, and David Skeie. 2011. "Bank Liquidity, Interbank Markets, and Monetary Policy." *Review of Financial Studies*, 24(8): 2656–2692.

Freixas, Xavier, Bruno Parigi, and Jean-Charles Rochet. 2000. "Systemic Risk, Interbank Relations, and Liquidity Provision by the Central Bank." *Journal of Money, Credit and Banking*, 32(3): 611–638.

Freixas, Xavier, Curzio Giannini, Glenn Hoggarth, and Farouk Soussa. 2000. "Lender of last resort: what have we learned since Bagehot?" *Journal of Financial Services Research*, 18(1): 63–84.

Freixas, Xavier, Jean-Charles Rochet, and Bruno M Parigi. 2004. "The Lender of Last Resort: A Twenty-First Century Approach." *Journal of the European Economic Association*, 2(6): 1085–1115.

Gai, Prasanna. 2013. *Systemic Risk: The Dynamics of Modern Financial Systems.* Oxford: Oxford University Press.

Gai, Prasanna, Andrew Haldane, and Sujit Kapadia. 2011. "Complexity, concentration and contagion." *Journal of Financial Economics*, 58(5): 453–470.

Gai, Prasanna, and Sujit Kapadia. 2010. "Contagion in financial networks." *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 466(2120): 2401–2423.

Gale, Douglas, and Shachar Kariv. 2007. "Financial Networks." *The American Economic Review*, 97(2): 99–103.

Gale, Douglas, and Tanju Yorulmazer. 2013. "Liquidity hoarding." *Theoretical Economics*, 8(2): 291–324.

Galeotti, Andrea, and Fernando Vega-Redondo. 2011. "Complex networks and local externalities: A strategic approach." *International Journal of Economic Theory*, 7(1): 77–92.

Galeotti, Andrea, Sanjeev Goyal, and Jurjen Kamphorst. 2006. "Network formation with heterogeneous players." *Games and Economic Behavior*, 54(2): 353–372.

Galeotti, A., Sanjeev Goyal, Matthew O Jackson, F Vega-Redondo, and Leeat Yariv. 2010. "Network games." *The Review of Economic Studies*, 77(1): 218–244.

Georg, Co-Pierre. 2014. *Contagious herding and endogenous network formation in financial networks.* Deutsche Bundesbank Discussion Paper, No. 23/2014, available at: http://www.bundesbank.de/Redaktion/EN/Downloads/Publications/Discussion_Paper_1/2014/2014_09_05_dkp_23.pdf?__blob=publicationFile [Accessed: 7 November 2014].

Gilbert, E N. 1959. "Random Graphs." *Annals of Mathematical Statistics*, 30(4): 1141–1144.

Gintis, Herbert. 2000. *Game theory evolving: A problem-centered introduction to modeling strategic interaction.* Princeton, NJ: Princeton University Press.

Glasserman, Paul, and H Peyton Young. 2015. "How likely is contagion in financial networks?" *Journal of Banking & Finance*, 50: 383–399.

Golub, Benjamin, and Matthew O Jackson. 2010. "Naïve Learning in Social Networks and the Wisdom of Crowds." *American Economic Journal: Microeconomics*, 2(1): 112–149.

Goyal, Sanjeev. 2007. *Connections: An Introduction to the Economics of Networks.* Princeton, Oxford: Princeton University Press.

Goyal, Sanjeev, and Fernando Vega-Redondo. 2005. "Network formation and social coordination." *Games and Economic Behavior*, 50(2): 178–207.

Gracia-Lázaro, Carlos, José A Cuesta, Angel Sanchez, and Yamir Moreno. 2012. "Human behavior in Prisoner's Dilemma experiments suppresses network reciprocity." *Scientific Reports*, 2(325): 1–4.

Granovetter, Mark. 1985. "Economic Action and Social Structure: The Problem of Embeddedness." *American Journal of Sociology*, 91(3): 481–510.

Gropp, Reint, Christian Gruendl, and Andre Guettler. 2014. "The Impact of Public Guarantees on Bank Risk-Taking: Evidence from a Natural Experiment*." *Review of Finance*, 18: 457–488.

Grujić, Jelena, Constanza Fosco, Lourdes Araujo, José A Cuesta, and Angel Sanchez. 2010. "Social Experiments in the Mesoscale: Humans Playing a Spatial Prisoner's Dilemma." *PLoS ONE*, 5(11): e13749.

Halaj, Grzegorz, and Christoffer Kok. 2014. "Modelling the emergence of the interbank networks." *Quantitative Finance*, 15(4): 653–671.

Haldane, Andrew G, and Robert M May. 2011. "Systemic risk in banking ecosystems." *Nature*, 469(7330): 351–355.

Hamilton, William D. 1963. "The Evolution of Altruistic Behavior." *The American Naturalist*, 97(896): 354–356.

Hamilton, William D. 1967. "Extraordinary sex ratios." *Science*, 156: 477–488.

Hardin, Garrett. 1968. "The Tragedy of the Commons." *Science*, 162: 1243–1248.

Heider, Florian, Marie Hoerova, and Cornelia Holthausen. 2009. *Liquidity Hoarding and Interbank Market Spreads. The Role of Counterpary Risk.* ECB Working Paper Series, No. 1126, available at: http://www.ecb.int/pub/pdf/scpwps/ecbwp1126.pdf [Accessed: 22 February 2012].

HM Treasury. 2012. *Banking reform: delivering stability and supporting a sustainable economy.* White Paper, available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/32556/whitepaper_banking_reform_140512.pdf [Accessed: 11 July 2013].

Hojman, Daniel A, and Adam Szeidl. 2006. "Endogenous networks, social games, and evolution." *Games and Economic Behavior*, 55(1): 112–130.

Hojman, Daniel A, and Adam Szeidl. 2008. "Core and periphery in networks." *Journal of Economic Theory*, 139(1): 295–309.

Holmström, Bengt, and Jean Tirole. 1998. "Private and Public Supply of Liquidity." *The Journal of Political Economy*, 106(1): 1–40.

Hüser, Anne-Caroline. 2015. *Too Interconnected to Fail: A Survey of the Interbank Networks Literature* . SAFE Working Paper, No. 91, House of Finance, Goethe University, available at: http://ssrn.com/abstract=2577241 [Accessed: 23 March 2015].

in't Veld, Daan Laurens, Marco van der Leij, and Cars H Hommes. 2014. *The Formation of a Core Periphery Structure in Heterogeneous Financial Networks.* Working Paper, available at: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2473131 [Accessed: 11 November 2014].

Iori, Giulia, and Saqib Jafarey. 2001. "Criticality in a model of banking crises." *Physica A: Statistical Mechanics and its Applications*, 299(1–2): 205–212.

Iori, Giulia, Rosario N Mantegna, Luca Marotta, Salvatore Micciche, James Porter, and Michele Tumminello. 2015. "Networked relationships in the e-MID interbank market: A trading model with memory ." *Crises and ComplexityComplexity Research Initiative for Systemic InstabilitieS (CRISIS) Workshop 2013*, 50: 98 –116.

Iyer, Rajkamal, and Jose-Luis Peydro. 2011. "Interbank Contagion at Work: Evidence from a Natural Experiment." *Review of Financial Studies*, 24(4): 1337–1377.

Jackson, Matthew O. 2003. *A Survey of Models of Network Formation: Stability and Efficiency.* Working Paper, available at: http://authors.library.caltech.edu/12791/1/JACgfe04.pdf [Accessed: 13 February 2012].

Jackson, Matthew O. 2008. *Social and Economic Networks.* Princeton, Oxford: Princeton University Press.

Jackson, Matthew O. 2010. *An Overview of Social Networks and Economic Applications.* Working Paper, available at: http://www.stanford.edu/ jacksonm/socialnetecon-chapter.pdf [Accessed: 31 May 2012].

Jackson, Matthew O, and Alison Watts. 2002*a*. “On the formation of interaction networks in social coordination games.” *Games and Economic Behavior*, 41(2): 265–291.

Jackson, Matthew O, and Alison Watts. 2002*b*. “The Evolution of Social and Economic Networks.” *Journal of Economic Theory*, 106(2): 265–295.

Jackson, Matthew O, and Asher Wolinsky. 1996. “A Strategic Model of Social and Economic Networks.” *Journal of Economic Theory*, 71: 44–74.

Jackson, Matthew O, and Leeat Yariv. 2007. “Diffusion of Behavior and Equilibrium Properties in Network Games.” *The American Economic Review*, 97(2): 92–98.

Jackson, Matthew O, and Yves Zenou. 2014. “Games on Networks.” In *Handbook of game theory*, edited by H Peyton Young and Shmuel Zamir. Amsterdam et al.: Elsevire Science.

Kandori, Michihiro, George J Mailath, and Rafael Rob. 1993. “Learning, Mutation, and Long Run Equilibria in Games.” *Econometrica*, 61(1): 29–56.

Kearns, Michael, Michael L Littman, and Satinder Singh. 2001. “Graphical models for game theory.” *Proceedings of the Seventeenth conference on Uncertainty in artificial intelligence*, 253–260.

Keeley, Michael C. 1990. “Deposit Insurance, Risk, and Market Power in Banking.” *The American Economic Review*, 80(5): 1183–1200.

King, Michael R, Steven Ongena, and Nikola Tarashev. 2016. *Bank Standalone Credit Ratings.* BIS Working Paper Series, No 542, available at: http://wwwbisorg/publ/work542pdf [Accessed: 1 May 2016].

Körner, Tobias, and Isabel Schnabel. 2013. *Abolishing Public Guarantees in the Absence of Market Discipline.* Working Paper, available at: https://www.econstor.eu/dspace/bitstream/10419/83672/1/769094856.pdf [Accessed: 4 May 2016].

Kovalenko, I N. 1971. “Theory of random graphs.” *Kibernetika*, 4: 1-4 (in Russian). English transl. Cybernetics, 7: 575-579.

Kozma, Balazs, and Alain Barrat. 2008. “Consensus formation on adaptive networks.” *Physical Review E*, 77(016102): 1–10.

Ladley, Daniel. 2013. “Contagion and risk-sharing on the inter-bank market.” *Journal of Economic Dynamics and Control*, 37(7): 1384–1400.

Leitner, Yaron. 2005. “Financial Networks: Contagion, Commitment, and Private Sector Bailouts.” *The Journal of Finance*, 60(6): 2925–2953.

López-Pintado, Dunia. 2008. “The Spread of Free-Riding Behavior in a Social Network.” *Eastern Economic Journal*, 34(4): 464–479.

Macy, Michael W. 1991. “Learning to Cooperate: Stochastic and Tacit Collusion in Social Exchange.” *American Journal of Sociology*, 97(3): 808–843.

Macy, Michael W. 2002. “Learning dynamics in social dilemmas.” *Proceedings of the National Academy of Sciences*, 99: 7229–7236.

Maynard Smith, J., and G. R. Price. 1973. “The Logic of Animal Conflict.” *Nature*, 246: 15–18.

Maynard Smith, John, and G. A. Parker. 1976. “The logic of asymmetric contests.” *Animal Behaviour*, 24: 159–175.

May, Robert M. 1973. *Stability and complexity in model ecosystems.* Princeton: Princeton University Press.

May, Robert M. 2013. “Networks and webs in ecosystems and financial systems.” *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 371(1987): 20120376.

May, Robert M, S Bohoeffer, and Martin A Nowak. 1995. “Spatial games and evolution of cooperation.” *Proceedings of the Third European Conference on Advances in Artificial Life*, 929: 749–759.

May, Robert, Simon A Levin, and G Sugihara. 2008. “Ecology for bankers.” *Nature*, 451(21): 893–895.

Mehran, Hamid, Alan Morrison, and Joel Shapiro. 2012. “Corporate Governance and Banks: What Have We Learned from the Financial Crisis?” In *The Crisis Aftermath: New Regulatory Paradigms*, edited by Mathias Dewatripont and Xavier Freixas, 11–44. London: Centre for Economic Policy Research.

Minoiu, Camelia, and Javier A Reyes. 2013. “A network analysis of global banking: 1978–2010.” *Journal of Financial Stability*, 9(2): 168–184.

Mistrulli, Paolo Emilio. 2011. “Assessing financial contagion in the interbank market: Maximum entropy versus observed interbank lending patterns.” *Journal of Financial Economics*, 35(5): 1114–1127.

Nash, John. 2015. *Liquidity Sharing and Financial Contagion.* Working Paper, available at: http://faculty.chicagobooth.edu/workshops/finance/pdf/Nash%20Liquidity%20Sharing.pdf [Accessed: 4 November 2015].

Nash, John F. 1950. “The Bargaining Problem.” *Econometrica*, 18(2): 155–162.

Newman, Mark. 2010. *Networks: An Introduction.* Oxford: Oxford University Press.

Nier, Erlend, Jing Yang, Tanju Yorulmazer, and Amadeo Alentorn. 2007. “Network models and financial stability.” *Journal of Financial Economics*, 31(6): 2033–2060.

Nowak, Martin A. 2006*a*. *Evolutionary Dynamics: Exploring the Equations of Life.* Cambridge, MA; London: The Belknap Press of Harvard University Press.

Nowak, Martin A. 2006*b*. “Five Rules for the Evolution of Cooperation.” *Science*, 314: 1560–1563.

Nowak, Martin A, and Karl Sigmund. 1992. “Tit for tat in heterogeneous populations.” *Nature*, 355: 250–253.

Nowak, Martin A, and Karl Sigmund. 1998. “Evolution of indirect reciprocity by image scoring.” *Nature*, 393: 573–577.

Nowak, Martin A, S. Bonhoeffer, and R.M. May. 1994. "Spatial games and the maintenance of cooperation." *Proceedings of the National Academy of Sciences*, 91(11): 4877–4881.

Onnela, Jukka-Pekka, and Felix Reed-Tsochas. 2010. "Spontaneous emergence of social influence in online systems." *Proceedings of the National Academy of Sciences*, 107(43): 18375–18380.

Petersen, Mitchell A, and Raghuram G Rajan. 2012. "The Benefits of Lending Relationships: Evidence from Small Business Data." *The Journal of Finance*, 49(1): 3–37.

Podolny, Joel M. 1993. "A Status-Based Model of Market Competition." *The American Journal of Sociology*, 98(4): 829–872.

Podolny, Joel M. 2005. *Sociological Signals: A Sociological Study of Market Competition.* Princeton: Princeton University Press.

Rajaraman, R. 1987. *Solitons and Instantons. An Introduction to Solitons and Instantons in Quantum Field Theory.* Amsterdam et al.: North Holland Personal Library.

Rapoport, A, and A M Chammah. 1965. *Prisoner's dilemma.* Ann Arbor: University of Michigan Press.

Rochet, Jean-Charles, and Jean Tirole. 1996. "Interbank Lending and Systemic Risk." *Journal of Money, Credit and Banking*, 28(4): 733–762.

Roukny, Tarik, Co-Pierre Georg, and Stefano Battiston. 2014. *A network analysis of the evolution of the German interbank market.* Deutsche Bundesbank Discussion Paper, No. 22/2014, available at: http://www.bundesbank.de/Redaktion/EN/Downloads/Publications/Discussion_Paper_1/2014/2014_09_05_dkb_22.pdf?_blob=publicationFile [Accessed: 3 November 2014].

Saavedra, Serguei, David Smith, and Felix Reed-Tsochas. 2010. "Cooperation under Indirect Reciprocity and Imitative Trust." *PLoS ONE*, 5(10): e13475–1–6.

Saavedra, Serguei, Rudolf P Rohr, Luis J Gilarranz, and Jordi Bascompte. 2014. "How structurally stable are global socioeconomic systems?" *Journal of The Royal Society Interface*, 11(100): 20140693.

Samuelson, Larry. 1998. *Evolutionary Games and Equilibrium Selection.* Cambridge, MA; London: MIT Press.

Saramaki, Jari, E A Leicht, Eduardo López, Sam G B Roberts, Felix Reed-Tsochas, and Robin I M Dunbar. 2014. "Persistence of social signatures in human communication." *Proceedings of the National Academy of Sciences*, 111(3): 942–947.

Schlierbach, Helmut, and Günter Püttner. 2003. *Das Sparkassenrecht in der Bundesrepublik Deutschland.* 5th ed., Stuttgart: Deutscher Sparkassenverlag.

Schweitzer, F, G Fagiolo, D Sornette, F Vega-Redondo, A Vespignani, and DR White. 2009. "Economic networks: The new challenges." *Science*, 325: 422.

Shapiro, Joel, and David Skeie. 2015. "Information Management in Banking Crises." *Review of Financial Studies*, 10.1093/rfs/hhv010.

Shiller, Robert J. 2015. *Irrational Exuberance.* Revised and expanded third ed., Princeton: Princeton University Press.

Singh, Jasjit. 2005. "Collaborative Networks as Determinants of Knowledge Diffusion Patterns." *Management Science*, 51(5): 756–770.

Skyrms, Brian. 1996. *Evolution of the social contract.* Cambridge: Cambridge University Press.

Smerlak, Matteo, Brady Stoll, Agam Gupta, and James S Magdanz. 2015. "Mapping Systemic Risk: Critical Degree and Failures Distribution in Financial Networks." *PLoS ONE*, 10(7): e0130948.

Stepanov, V E. 1969. "Combinatorial Algebra and random graphs." *Theory Probab. Applics*, 14: 373–399.

Stepanov, V E. 1970*a*. "On the probability of connectedness of a random graph G_m(t)." *Theory Probab. Applics*, 15: 55–67.

Stepanov, V E. 1970*b*. "Phase transitions in random graphs." *Theory Probab. Applics*, 15: 187–203.

Sugden, Robert. 1984. "Reciprocity: The Supply of Public Goods Through Voluntary Contributions." *The Economic Journal*, 94(376): 772–787.

Szabó, György, and Gábor Fáth. 2007. "Evolutionary games on graphs." *Physics Reports*, 446(4-6): 97–216.

Thurner, Stefan, and Sebastian Poledna. 2013. "DebtRank-transparency: Controlling systemic risk in financial networks." *Scientific Reports*, 3(1888).

Upper, Christian. 2011. "Simulation methods to assess the danger of contagion in interbank markets." *Journal of Financial Stability*, 7(3): 111–125.

Upper, Christian, and Andreas Worms. 2004. "Estimating bilateral exposures in the German interbank market: Is there a danger of contagion?" *Journal of Financial Economics*, 48(4): 827–849.

Watts, Alison. 1999. "A Dynamic Model of Network Formation." *Games and Economic Behavior*, 34(2): 331–341.

Wegner, Danilo Lopomo Beteto. 2014. *Network Formation and Financial Fragility.* Working Paper, available at: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2480767 [Accessed: 11 November 2014].

Weibull, Jörgen W. 1995. *Evolutionary Game Theory.* Cambridge, MA; London: MIT Press.

West, Stuart A., Claire El Mouden, and Andy Gardner. 2011. "Sixteen common misconceptions about the evolution of cooperation in humans." *Evolution and Human Behavior*, 32(4): 231–262.

Young, H Peyton. 1993*a*. "An Evolutionary Model of Bargaining." *Journal of Economic Theory*, 59: 145–168.

Young, H Peyton. 1993*b*. "The Evolution of Conventions." *Econometrica*, 61(1): 57–84.

Young, H Peyton. 1998. *Individual Strategy and Social Structure: An Evolutionary Theory of Institutions.* Princeton: Princeton University Press.

Young, H Peyton. 2011. "The dynamics of social innovation." *Proceedings of the National Academy of Sciences*, 108(4): 21285–21291.

Zawadowski, Adam. 2013. "Entangled Financial Systems." *Review of Financial Studies*, 26(5): 1291–1323.

Zhong, Weicai, Hussein A Abbass, Axel Bender, and Jing Liu. 2011. "Mixed strategy and coevolution dynamics in social networks." *Physica A: Statistical Mechanics and its Applications*, 390(2): 410–417.