House of Finance

Working Paper Series

Anne-Caroline Hüser

Too Interconnected to Fail: A Survey of the Interbank Networks Literature

SAFE Working Paper No. 91

SAFE | Sustainable Architecture for Finance in Europe
A cooperation of the Center for Financial Studies and Goethe University Frankfurt

House of Finance | Goethe University
Theodor-W.-Adorno-Platz 3 | 60323 Frankfurt am Main

Tel. +49 69 798 34006 | Fax +49 69 798 33910
info@safe-frankfurt.de | www.safe-frankfurt.de

Non-technical summary

A network approach to banking is particularly important for assessing financial stability and systemic risk. This approach can be instrumental in capturing the externalities that the risk associated with a single institution may create for the entire system. Indeed, from a financial stability perspective, banks should neither be too-big-to-fail nor too-interconnected-to-fail. A better understanding of network externalities may facilitate the adoption of a macro-prudential framework for financial supervision. Network externalities arise when risk-taking behavior of individual institutions affects other institutions and the system as a whole. To guide policy it becomes necessary, in this context, to measure the systemic importance of individual banks, i.e. their capacity to generate contagion in the rest of the system. The analysis of interbank networks can provide this guidance.

Against this background we review the literature on interbank networks, which is part of a growing literature on financial networks. The broader financial networks literature is analyzing connections between financial institutions: banks, but also hedge funds, insurance companies, etc. We restrict the survey's focus on the interbank network literature. This survey presents a systematic overview of our current understanding of the structure of interbank networks, of how network characteristics affect contagion in the banking system and of how banks form connections when faced with the possibility of contagion and systemic risk. In particular, we highlight how the theoretical literature on interbank networks offers a coherent way of studying interconnections, contagion processes and systemic risk, while emphasizing at the same time the many challenges that must be addressed before general results on the link between the structure of the interbank network and financial stability can be established.

The theoretical literature has generated a number of insights on the effect of the network structure on contagion. A first result is that the number and magnitude of defaults depend on the network topology. There is now substantial research characterizing those structures that tend to propagate default or alternatively that tend to dampen it. An avenue for further research is to have more realistic network structures on which to analyze contagion. Since empirical studies now provide an increasing number of stylized facts on the interbank network topology, research needs to move beyond deriving results on random networks or on overly simplified structures. Furthermore, the fragility of the system depends on the location in the network of the institution that was initially affected. Intuitively, the failure of core banks is more damaging than the failure of a periphery bank. Finally, another main finding is that there is a trade-off between risk sharing via linkages to other banks and contagion risk due to too many linkages. While the existence of the trade-off is not disputed, there is no consensus on whether a complete network dampens or fuels contagion. Some studies argue that intermediate levels of connectivity are better, for example because the effect of connectivity on contagion is non-monotonic. Recent research argues that a complete network is more resilient to small shocks whereas in the presence of large shocks, less connections are better able to prevent contagion. The lack of consensus hinges on the fact that these studies have been conducted on widely different network structures and under different assumptions about the size and type of shocks. Again, conducting analyses on more realistic network structures is required to make a convincing case.

Another shortcoming is that most interbank network models in the literature are static and exogenously given. One limitation of these static models is that they do not provide a dynamic account of link formation. Research is moving in this direction, but most of the dynamic models still use probabilistic link formation by relying on network growth models or on preferential attachment rules. A few recent models rely on endogenous network formation, in which banks purposefully choose the amount of interbank lending and borrowing and thereby create the structure of the interbank network. More work is needed on how to incorporate bank behavior into interbank networks. More precisely, we need to include micro-founded models of bank's dynamic reactions to financial shocks and to changes in regulatory parameters.

The survey concludes with a discussion of the policy relevance of interbank network models with a special focus on macro-prudential policies and monetary policy. Being able to capture heterogeneity and interconnectedness, the network literature can be a useful source for policy insights on financial stability. As data availability improves, it is possible to get increasingly accurate network representations of the underlying financial system. The interbank networks literature focuses on four main policy areas. The first is identifying critical institutions, where measures of centrality and clustering are used to identify the systemically relevant banks in the network. The second policy area we discuss is stress testing and how supervisory authorities can gather insights from network models for stress testing exercises. The third focus is on monetary policy. Central banks are introduced into the interbank network by allowing one bank either to supply an unlimited amount of liquidity or to provide liquidity against eligible collateral. The fourth and most studied area focuses on macro-prudential policy. The theoretical network literature has done policy experiments to simulate the impact of different regulatory measures on systemic risk. More research is needed to evaluate the impact of macro-prudential policy instruments on the banking sector as well as the analysis of the interactions between different macro-prudential policy instruments. Similarly, the evaluation of the interactions between monetary policy and macro-prudential policy is also an interesting topic for further research.

Too Interconnected to Fail: A Survey of the Interbank Networks Literature*

Anne-Caroline Hüser†

Abstract

The banking system is highly interconnected and these connections can be conveniently represented as an interbank network. This survey presents a systematic overview of the recent advances in the theoretical literature on interbank networks and assesses our current understanding of the structure of interbank networks, of how network characteristics affect contagion in the banking system and of how banks form connections when faced with the possibility of contagion and systemic risk. In particular, I highlight how the theoretical literature on interbank networks offers a coherent way of studying interconnections, contagion processes and systemic risk, while emphasizing at the same time the challenges that must be addressed before general results on the link between the structure of the interbank network and financial stability can be established. The survey concludes with a discussion of the policy relevance of interbank network models with a special focus on macro-prudential policies and monetary policy.

Keywords: Interbank networks; systemic risk; contagion; banking; macro-prudential policy

JEL codes: G21; E44; D85; G18; G01

*I am grateful to Iñaki Aldasoro, Michael Gofman, Grzegorz Halaj, Markus Kontny, Marie Lalanne, Martin Scheicher and Nicolas Scholtes for helpful suggestions and to Ester Faia for introducing me to interbank networks. I gratefully acknowledge research support from the Research Center SAFE, funded by the State of Hessen initiative for research LOEWE.

† *Goethe University Frankfurt & SAFE.* Email: `annecaroline.hueser@gmail.com`; Address: House of Finance, Goethe University, Theodor-W.-Adorno-Platz 3, 60629 Frankfurt am Main, Germany.

Contents

1 Introduction **1**

2 Interbank network structure and topology **5**
2.1 Overview of features particular to interbank networks 5
2.2 Selected empirical findings on the structure of interbank networks 6
2.2.1 Degree distribution 6
2.2.2 Core-periphery structures 7
2.3 Multilayer interbank networks 8

3 Effect of network structure on contagion **12**
3.1 Direct linkages 12
3.1.1 Pioneering works: Are more links always better? 13
3.1.2 Network characteristics and contagion 15
3.1.3 Beyond standard default cascades 15
3.2 Indirect linkages 17
3.3 Interactions between direct and indirect linkages 18
3.3.1 Models incorporating the fire sales mechanism by Cifuentes et al. (2005) 18
3.3.2 Other models with direct and indirect links 19

4 Network formation **22**
4.1 Relationship lending and random network formation 23
4.2 Strategic network formation and rollover risk 23
4.3 Strategic network formation and excessive counterparty risk 24
4.4 Network formation via portfolio optimization 26

5 Policy insights from interbank networks **27**
5.1 Identifying critical institutions 28
5.2 Stress testing 28
5.3 Insights for monetary policy 29
5.4 Insights for macro-prudential policy 30
5.4.1 Liquidity requirements 30
5.4.2 Limiting counterparty risk 31
5.4.3 Capital requirements 32

6 Conclusion **33**

List of Tables

1 **Empirical Literature on the Topology of the Interbank Network** 11
2 **Theoretical Interbank Network Literature** (D=direct, I=indirect) . 21

1 Introduction

Why model the banking sector as a network? Banks are highly interdependent, they are connected via both the asset and the liability sides of their balance sheets. For example, credit exposure on the interbank market create links between banks. These connections can be conveniently represented as a network.[1] Such a network approach to banking is particularly relevant for assessing financial stability and systemic risk (Allen and Babus, 2009; Haldane, 2009). This approach can be instrumental in capturing the externalities that the risk associated with a single institution may create for the entire system. Indeed, from a financial stability perspective, banks should neither be too-big-to-fail nor too-interconnected-to-fail. A better understanding of network externalities may facilitate the adoption of a macro-prudential framework for financial supervision. Network externalities arise when risk-taking behaviour of individual institutions affects other institutions and the system as a whole. To guide policy it becomes necessary, in this context, to measure the systemic importance of individual banks, i.e. their capacity to generate contagion in the rest of the system. The analysis of interbank networks can provide this guidance.

In their survey on systemic risk in banking De Bandt et al. (2012) put forward a 'financial fragility hypothesis', arguing that systemic risk and potential contagion effects are of special concern in the financial system. They highlight three interrelated features that provide a basis for the 'financial fragility hypothesis'. This survey argues that these three features can all be captured by interbank network models, making these models particularly appealing for financial stability research. One feature that makes the financial system fragile according to De Bandt et al. (2012) is that there is a 'complex network of exposures among banks'. Interbank network models are clearly able to capture these complex exposures, for example by representing different maturities and instruments at the same time (Aldasoro and Alves, 2015; Langfield et al., 2014; Montagna and Kok, 2013) and including several contagion channels (Cifuentes et al., 2005; Gai and Kapadia, 2010; Glasserman and Young, 2015). The second feature that leads to a fragile financial system is that the maturity transformation activity performed by banks makes the structure of the bank's balance sheet matter. This makes miscoordination of depositors and creditors costly. Network studies have analyzed these problems, for example by studying bank runs (Dasgupta, 2004), short-term lending (Battiston et al., 2012a), maturity transformation (Georgescu, 2015) and rollover risk (Anand et al., 2012; Allen et al., 2012). Interbank network models also incorporate the balance sheet structures of banks at increasing levels of sophistication. Recent models feature banks optimizing their balance sheet and thereby endogenously creating the interbank network (Bluhm et al., 2014a; Bräuning et al., 2015; Georg, 2013). The third and last feature highlighted by De Bandt et al. (2012) is the 'informational and control intensity of financial contracts, which rely on promises and expectations about future payments'. The role of uncertainty (Caballero and Simsek, 2013), increasing counterparty risk (Hałaj and Kok,

[1] Networks are constituted of nodes and links between these nodes. In the case of interbank networks, the nodes represent banks and the links represent the interbank relations.

2015) and liquidity hoarding (Aldasoro et al., 2015; Gai et al., 2011) can all be explored in interbank network models. Hence the interbank network literature can help understand systemic risk in all its facets and can therefore be relevant not only for academic research but also for practitioners.

This survey reviews the literature on interbank networks, which is part of a growing literature on financial networks. The broader financial networks literature is analyzing connections between financial institutions: banks, but also hedge funds, insurance companies, etc.[2] This survey focuses on the interbank network literature and takes stock of our current understanding of the topology of interbank networks, of how its structure affects contagion and of how banks form connections when faced with the possibility of contagion and systemic risk. For each aspect a brief overview of the results is provided and avenues for further research are highlighted. A final section reviews and discusses the policy insights gained from the interbank network literature.

The first section of this survey reviews empirical work, which provides a direct insight into the topology of real interbank networks. The structural features of the banking system can be particularly well captured by a network representation. The network is able to represent the fact that banks have heterogeneous balance sheet characteristics. Networks can also capture that links between banks are directed, since it is economically meaningful whether a bank borrows from or lends to another bank. Furthermore, networks also allow for weighted links between banks, where the weights are the monetary quantities that banks exchange. Finally, a network representation can also incorporate the different types of links between banks. As Langfield and Soramäki (2014) highlight, banks engage in hundreds of different types of transactions with each other, such as interbank lending, repurchase agreements or derivatives. This plethora of possible link types can be captured by multilayer financial networks, where different layers represent different transaction types (Aldasoro and Alves, 2015; Bargigli et al., 2014; Langfield et al., 2014; Montagna and Kok, 2013). Empirical studies have also provided new insights into the structure of interbank networks. A major result is that interbank networks exhibit a core-periphery structure with a highly connected core and few connections to and among periphery banks (Craig and von Peter, 2014; Fricke and Lux, 2015a; Langfield et al., 2014; Veld and van Lelyveld, 2014).

The second section of this survey discusses the theoretical literature on the effect of network characteristics on the process of contagion. The theoretical literature has generated a number of general results on this question. A first result is that the number and magnitude of defaults depend on the network topology. There is now substantial research characterizing those structures that tend to propagate default or alternatively that tend to dampen it (Allen and Gale, 2000; Acemoglu et al., 2015a; Freixas et al., 2000; Gai et al., 2011; Nier et al., 2007). An avenue for further research is to have more realistic network structures on which to analyze contagion. Since empirical studies now provide an increasing number of stylized facts on the interbank network topology, research needs to move beyond deriving results on random networks or on overly simplified structures[3].

[2] See for example Billio et al. (2012).

[3] Prominent structures include the complete network, the star network and the ring network.

Furthermore, the fragility of the system depends on where the initially affected node is located in the system (Gai and Kapadia, 2010). Intuitively, the failure of core banks is more damaging than the failure of a periphery bank. Finally, another main finding is that there is a trade-off between risk sharing via linkages to other banks and contagion risk due to too many linkages. While the existence of the trade-off is not disputed, there is no consensus on whether a complete network dampens (Allen and Gale, 2000; Freixas et al., 2000) or fuels contagion (Battiston et al., 2012b; Vivier-Lirimont, 2006). Some studies argue that intermediate levels of connectivity are better, for example because the effect of connectivity on contagion is non-monotonic (Gai et al., 2011; Nier et al., 2007). Recent research by Acemoglu et al. (2015a) argues that a complete network is more resilient to small shocks whereas in the presence of large shocks, less connections are better able to prevent contagion. The lack of consensus hinges on the fact that these studies have been conducted on widely different network structures and under different assumptions about the size and type of shocks.[4] Again, conducting analyses on more realistic network structures is required to make a convincing case. The question that remains is how banks strategically trade off risk sharing and contagion risk. This topic has been taken up recently by the literature on network formation.

The third section argues that one limitation of static models of financial networks is that they do not provide an account of link formation. More precisely, they do not model the dynamic process by which financial institutions enter into obligations to one another in the first place. So far, three main approaches to link formation have crystallized in the financial networks literature. One branch of the literature uses random link formation. Typically, these are random network models where new nodes are born over time and form attachments to existing nodes with a certain probability. A second area uses strategic network formation, where banks assess the costs and benefits from forming a link with another bank (Blume et al., 2013). A prominent theme in strategic network formation are rollover decisions by banks, often modeled using global games techniques. Creditors strategically decide to rollover a loan after receiving a signal about the solvency or performance of the borrower (Allen et al., 2012; Anand et al., 2012; Fique and Page, 2013). Also using strategic network formation, Farboodi (2014) and Acemoglu et al. (2015b) show how equilibrium networks may exhibit excessive counterparty risk. The third area builds network formation on the basis of portfolio optimization by financial institutions (Aldasoro et al., 2015; Bluhm et al., 2014a,b; Bräuning et al., 2015; Hałaj and Kok, 2015).

The fourth section discusses the policy insights from the interbank networks literature. The focus is on four main policy areas. The first is identifying critical institutions, where measures of centrality and clustering are used to identify the systemically relevant banks in the network.[5] The second policy area of interest is stress testing and how supervisory authorities can gather insights from network models for stress testing exercises (Anand et al., 2014; Canedo and Jaramillo, 2009; Chan-Lau et al., 2009; Espinosa-Vega

[4]See Table 2 for an overview of the different types of shocks and network structures used in this literature.

[5]See Langfield and Soramäki (2014) for a survey of these measures.

and Solé, 2014; Hałaj and Kok, 2015). The third focus is on monetary policy. Central banks are introduced into the interbank network by allowing one bank either to supply an unlimited amount of liquidity (Bluhm et al., 2014b) or to provide liquidity against eligible collateral (Georg, 2013). The final and most studied area focuses on macro-prudential policy. The theoretical network literature has done policy experiments to simulate the impact of different regulatory measures on systemic risk (Aldasoro et al., 2015; Gai et al., 2011; Gofman, 2014; Hałaj and Kok, 2015; Haldane and May, 2011; Nier et al., 2007).

After having briefly discussed the literature reviewed in this survey, let us now turn to an overview of the already existing surveys of the field. Considering the growing body of theoretical literature on financial networks, there have been remarkably few surveys on the subject. An early survey by Allen and Babus (2009) discusses the then emerging literature on financial networks as well as the methodologies used and makes a case why the complexity of financial systems can be 'naturally captured' using a network representation. The survey by Chinazzi and Fagiolo (2013) focuses on theoretical studies of the link between connectivity and stability in financial networks and therefore covers only a small subset of the theoretical papers reviewed here. Furthermore, roughly half of the hundred forty papers referenced here were published in 2013, 2014 or 2015 and to the best of my knowledge, there is no survey that has comprehensively taken stock of these new studies. Four other recent surveys are mainly focused on simulations of contagion in financial networks and their applications. Upper (2011) reviews simulation methods to test for contagion in empirical interbank networks as well as methods to construct interbank networks from different data sources. Elsinger et al. (2013) also survey simulated empirical financial networks and their applications in systemic risk analysis. Langfield and Soramäki (2014) review the empirical literature related to interbank markets from a systemic risk perspective. In addition to discussing network simulations, they also survey the literature on the topology of empirical interbank networks, as well as the literature for identifying systemically important banks. The survey by Summer (2013) also focuses on empirical simulation studies. Finally, the surveys on systemic risk by De Bandt et al. (2012) and Benoit et al. (2015) also include a discussion of financial network models alongside other modeling approaches used in that literature.

The present survey aims to fill this gap by providing a systematic overview of the theoretical interbank network literature. Table 2 classifies the theoretical interbank network literature by link type, shock type, loss propagation as well as by network formation process and network structure. The survey also provides a systematic discussion of the policy insights from theoretical network models. The survey is intended to be relevant not only for academic economists, but also for financial stability experts at central banks or supervisory authorities interested in the progress of the field and its potential policy relevance. Finally, this survey also builds a bridge between results from the financial network literature and the established macro finance literature.[6] Modeling techniques

[6]For an overview of the macro finance literature see for example the survey by Brunnermeier et al. (2013) or by Shin (2010). For a comprehensive collection of classic articles and recent contributions on liquidity and crises, see Allen et al. (2011).

in these two fields clearly differ. Network analysis can easily capture heterogeneity and interconnections, whereas the incorporation of optimizing financial institutions into networks is still in its infancy. The established macro finance literature can build on a long tradition of economic modeling of agent's decisions, with the restriction that agents are often representative. Still, both share similar research topics, for example the study of the propagation and amplification of shocks in the financial system, fire sales spirals, market liquidity or the fragility of financial intermediaries.

This survey is structured as follows. The next section takes stock of our current understanding of the topology of interbank networks. The third section reviews how the structure of the interbank network affects contagion. The fourth section analyzes how banks form connections when faced with the possibility of contagion and systemic risk. The fifth section reviews the policy insights gained from the interbank networks literature. The final section concludes by highlighting a few avenues for further research.

2 Interbank network structure and topology

Empirical work provides a direct insight into the topology of real interbank networks. Table 1 classifies the empirical literature on real interbank markets and summarizes the key topological features analyzed as well as key results.

2.1 Overview of features particular to interbank networks

The structural features of the banking system can be captured particularly well by a network representation. First, the network is able to represent the fact that banks have heterogeneous balance sheet characteristics. Banks will be of different sizes and have different compositions of assets and liabilities. Heterogeneous balance sheet characteristics imply heterogeneity in banks' inherent ability to withstand external shocks. Second, networks can also capture that links between banks are directed. Consider the simplest case where one bank lends to another bank. The first bank is exposed to the default of the second bank (counterparty risk), while the second bank might be exposed to the willingness of the first bank to rollover the loan (rollover risk). In both cases, the direction of the link does matter for economic interpretation. Third, networks also allow for weighted links between banks. A weighted link in this context means that links are associated with monetary quantities and transaction volumes. For example a weighted link between two banks can represent the size of the interbank loans between those two banks. Finally, a network representation can also incorporate the different types of links between banks. As Langfield and Soramäki (2014) highlight, banks engage in hundreds of different types of transactions with each other, including many variations on deposits; prime lending; repurchase agreements; and derivatives. This plethora of possible link types is now captured by recent research on multilayer financial networks (Aldasoro and Alves, 2015; Bargigli et al., 2014; Langfield et al., 2014; Montagna and Kok, 2013). In addition, banks are connected by virtue of their exposures to common risk factors. Banks are also connected across borders, but cross-border exposures are hard to quantify due to scarce data. Recent efforts have been directed for example at studying global banking from a network perspective (Garratt et al., 2014; Minoiu and Reyes, 2013) and at analyzing how international linkages in interbank markets affect the stability of interconnected banking systems (Tonzer, 2015). Furthermore, Abbassi et al. (2014) analyze the impact of financial crises and monetary policy on both the supply of wholesale funding liquidity and the compositional supply effects through cross-border lending using evidence from the Euro area interbank crisis.

The overall structure of interbank networks exhibits high clustering coefficients[7]. Real-world interbank networks are also sparse, which means that only a small fraction of all possible links do actually exist. The distribution of the number of connections of each node appears to be fat-tailed, meaning that few nodes have many links and many nodes have few links. Interbank networks have also been found to be small worlds[8] and to show disassortative mixing with respect to the bank size, so small banks tend to trade mainly with large banks and vice versa.[9]

2.2 Selected empirical findings on the structure of interbank networks

2.2.1 Degree distribution

The first selected feature is the degree distribution of the nodes. The degree is the number of (incoming and/or outgoing) connections per node, i.e. the number of the bank's counterparties. Boss et al. (2004) are the first to provide an empirical analysis of the structural features of a real-world interbank network using network theory. They analyze the Austrian interbank market based on central bank data. Their main finding is that the network structure of the interbank market is scale free[10]. This implies that there are very few banks with many interbank linkages, whereas there are many banks with only a few links. Many other existing interbank networks have been reported to resemble scale-free networks, such as the European interbank market for large banks (Alves et al., 2013), the Italian interbank market (De Masi et al., 2006), the Colombian payment and settlement systems (Léon and Berndsen, 2014) as well as the US Fedwire system (Soramäki et al., 2007).

Other studies by Bech and Atalay (2010), Iori et al. (2008) and Fricke and Lux (2015b) have nuanced these results. Studying the US Federal Funds market, Bech and Atalay (2010) have also found that the number of counterparties per bank follows a fat-tailed distribution, with most banks having few counterparties and a small number having many. However, the degree distribution is not necessarily best represented by a

[7]Clustering coefficients measure the tendency of linked nodes to have common neighbours.

[8]Small world networks have two main features: small average shortest path length and a clustering coefficient significantly higher than expected by random chance, see Watts and Strogatz (1998).

[9]A characteristic which is related to the core periphery structure of interbank networks as highlighted by Craig and von Peter (2014).

[10]A scale-free network is a network in which the fraction of nodes with degree k is proportional to $k^{-\alpha}$, where α is the so-called scaling parameter. In other words, scale-free networks exhibit a power law distribution of degrees. The term scale-free indicates that there is no typical scale of the degrees, i.e. the mean may not be representative.

power law distribution. While the power law distribution provides the best fit for the out-degree, the negative binomial distribution provides the best fit for the in-degree. Iori et al. (2008) and Fricke and Lux (2015b) find no evidence in favor of scale-free networks in the e-MID[11] market. Rather, Fricke and Lux (2015b) find that the data are best described by negative binomial distributions. Iori et al. (2008) find that the degree distribution, though not scale-free, is still heavier tailed than a purely random network[12].

In view of the mixed evidence regarding the power-law behavior, it is not settled whether real-world interbank networks fall into the category of scale-free networks. Knowing the degree distribution of interbank networks is crucial for policy design. As Albert et al. (2000) point out, scale-free networks are relatively robust to the random breakdown of nodes. At the same time, the system is very vulnerable to the risk of the specific removal of hubs, which can even lead to its collapse. This characteristic has been coined robust-yet-fragile (Haldane, 2009), indicating that random disturbances are easily absorbed (robust) whereas targeted attacks on the most central nodes may lead to a breakdown of the entire network (fragile). If interbank networks are scale-free, then identifying the vulnerable nodes is a key policy objective.

Thus, taking into account the relevance of such topological features, a more rigorous statistical analysis of the distributional properties of interbank network data should be worthwhile. It crucially hinges on the improved availability of more granular data. Of further interest are also the policy implications. For example, what does it mean for network stability to have a degree distribution that follows a negative binomial distribution? So far, the empirical literature has been silent on these questions.

2.2.2 Core-periphery structures

Numerous empirical studies find that interbank markets have a core-periphery structure: the German (Craig and von Peter, 2014), British (Langfield et al., 2014) and the Dutch (Veld and van Lelyveld, 2014) interbank markets, as well as the e-MID trading platform (Iori et al., 2008; Fricke and Lux, 2015a), the US federal funds market (Bech and Atalay, 2010) and the US Fedwire system (Soramäki et al., 2007) were found to exhibit this structure. The core-periphery structure is sometimes also called tiered or hierarchical structure in the network context.

Craig and von Peter (2014) capture this market structure by formulating a core-periphery model and devise a procedure for fitting the model to real-world networks. The banks in the system are partitioned into two sets based on their bilateral relations with each other: core banks lend to each other; periphery banks do not lend to each other; core banks lend to periphery banks; core banks borrow from periphery banks. Craig and

[11]The e-MID is an electronic trading system for unsecured deposits based in Milan and mainly used by Italian banks for overnight interbank credit.

[12]A random network is a network whose links are formed according to a random process. Such random networks are a useful benchmark against which we can contrast observed networks; such comparisons help to identify which elements of the interbank structure are not the result of mere randomness, but must be traced to other factors.

von Peter (2014) argue that tiering is founded on an economic concept that is central to banking, namely intermediation. Core banks are special intermediaries that play a central role in holding together the interbank market. The interbank market is often modeled in the theoretical banking literature as a centralized exchange in which banks smooth liquidity shocks (Ho and Saunders, 1985; Bhattacharya and Gale, 1987; Freixas and Holthausen, 2005). Craig and von Peter (2014) show that the interbank market looks very different from traditional banking models. The market is not a centralized exchange. It is in fact a sparse network, centered around a tight set of core banks that intermediate between numerous smaller banks in the periphery. Furthermore, this hierarchical structure is highly persistent over time (Craig and von Peter, 2014; Fricke and Lux, 2015a).

Theoretical models of the interbank market show the emergence of a core-periphery structure where banks form credit relationships based on trust in other banks (Lenzu and Tedeschi, 2012) or based on their willingness to lend (Lux, 2014). In't Veld et al. (2014) show that a core periphery network structure can form endogenously in a network formation game if agents are heterogeneous in size. Farboodi (2014) shows that if banks are heterogeneous in their access to a profitable investment opportunity, the equilibrium financial networks forms a core-periphery structure. [13]

2.3 Multilayer interbank networks

The vast majority of empirical financial networks papers studies the overnight interbank market. Yet this is just one type of relation between banks out of a multiplicity of transactions that banks engage in. Recent empirical studies hence argue that a more realistic representation of the interbank market is a multiplex, or multilayer network. A multilayer network is composed by a series of layers. Each node is a bank and each layer is a network representing one type of relation. Layers can represent maturity, nature of the contract (secured versus unsecured), instruments, direct and indirect links. This type of analysis crucially hinges on the availability of granular data. The main takeaway at this stage is that it is important to differentiate the layers of the network, since both topology and contagion processes can be different across layers. Table 1 presents an overview of the layers studied in the papers reviewed below.

Bargigli et al. (2014) exploit a database of supervisory reports on Italian banks that includes all bilateral exposures broken down by maturity and by the secured and unsecured nature of the contract. They find that layers have different topological properties and persistences over time. The topology of the total interbank market is very similar to the topology of the overnight market, while both provide little information about other layers. Furthermore, they find that different hubs operate in different segments, where hubs are defined as banks whose degree significantly exceeds the average. This suggests topological properties across the layers may hamper the diffusion of contagion. In general, the presence of a link in a layer is not a good predictor of the presence of

[13] See also Fricke and Lux (2015a) and Langfield et al. (2014) for a further discussion on why such core-periphery structures may emerge in interbank markets.

the same link in other layers. This finding calls for a careful analysis of the multi-layer features of the network before a final assessment of its robustness is made.

Aldasoro and Alves (2015) analyze data on exposures between large European banks, broken down by both maturity and instrument type. This multiplex network presents a high similarity between layers, stemming both from standard similarity analyses[14] as well as a core-periphery analysis of the different layers. They note that at the very top of the coreness ranking[15] they never find the same bank for any pair of networks when the focus is on either instrument or maturity type.

Molina-Borboa et al. (2015) come to the same conclusion in their analysis of a data set of Mexican interbank exposures. Similarly to Bargigli et al. (2014) and Aldasoro and Alves (2015), they find that the banks belonging to the cores of the different layers are not always the same. They also show that focusing on a single layer severely underestimates total systemic risk[16]. Montagna and Kok (2013) share the finding that focusing on a single interbank segment can underestimate the likelihood of contagion. They develop an agent-based model with the aim of capturing risks arising from different banks' businesses and calibrate it on a data set of large EU banks. The interbank market is represented as a multilayered network that takes into account long- and short-term bilateral exposures and common exposures to external financial assets. Montagna and Kok (2013) show that the interaction among layers may amplify contagion risk in those cases where certain institutions are systemically relevant across different segments.

Langfield et al. (2014) construct two networks from UK data: one based on multiple layers of exposures, by aggregating banks' counterparty credit risks; and another based on multiple layers of funding, by aggregating banks' funding from other banks. Structural differences in these two networks suggest that counterparty credit risk and liquidity risk propagate in the interbank network by different contagion processes, a finding shared for example by Montagna and Kok (2013) and Bargigli et al. (2014). The dataset also allows for an analysis of the structure of the interbank market by banks' sectors and by their role in the interbank market, as well as for an analysis by instrument class by means of cluster analysis. Their findings again point to the importance of considering different layers, as structure typically differs among them. For instance, how close the network resembles a core periphery structure depends on the asset class considered.

To conclude this section on empirical network studies, it is important to highlight that this literature analyzes the interbank network structure for particular countries. They provide valuable insights into topological features of real-world networks: realistic degree distributions, core-periphery structures, characteristics across maturities and instrument types. Hence empirical network studies form a vital basis for both empir-

[14] Aldasoro and Alves (2015) compute the Jaccard similarity index, which captures the probability of observing a given connection in a network conditional on observing the same link in the other network and the Cosine similarity index, which can be used as proximity metric.

[15] See Della Rossa et al. (2013) for a methodology assigning a coreness value to each node in a network.

[16] The systemic risk measure used is DebtRank, which was developed in Battiston et al. (2012c). In a nutshell, it measures the total economic value potentially lost by by the distress of a bank or a set of banks.

ical and theoretical simulation studies[17]. They also deliver valuable stylized facts and structural features for theoretical modeling, hence their relevance for this survey. Yet by construction, empirical studies are unable to draw general conclusions on the relationship between the characteristics of the financial system and contagion. This is the gap theoretical modeling can fill.

[17]See Upper (2011) and Summer (2013) for surveys on empirical simulation studies. In empirical simulation studies the interbank network is based on data and then adverse scenarios are simulated within this framework. In theoretical simulation studies, which are reviewed here, the interbank network is either given or generated by a model or stochastic process.

Paper	Scope	Data type	Frequency	Methodology[a]	Degree distribution[b]	Tiering	Multiple layers
Alves et al. (2013)	Large EU banks	Exposures			Power law[c]	No	No
Aldasoro and Alves (2015)	Large EU banks	Exposures		Craig and von Peter (2014)	Power law		Assets (ST,LT,R)[d] Derivatives (ST,LT,R) Off-balance sheet exposures (ST,LT,R)
Bargigli et al. (2014)	Italy	Transactions	Yearly		Power law (2.3)	Yes	Secured (ST,LT) Unsecured (OVT, ST, LT)[e]
Bech and Atalay (2010)	US federal funds	Payment	Daily	Furfine (1999)	Power law (out) Negative binomial (in)	Yes	No
Boss et al. (2004)	Austria	Balance sheet	Monthly	Maximum entropy	Power law (2.01)	Yes	No
Cont et al. (2013)	Brazil	Exposures	Irregular		Power law (2.54)		No
Craig and von Peter (2014)	Germany	Credit registry	Quarterly	Craig and von Peter (2014)		Yes	No
De Masi et al. (2006)	e-MID	Transactions	Overnight		Power law (2.3)	Yes	No
Fricke and Lux (2015b)	e-MID	Transactions	Daily		Negative binomial		No
Fricke and Lux (2015a)	e-MID	Transactions		Core-periphery algorithm(s)		Yes	No
Iori et al. (2008)	e-Mid	Transactions	Daily			Yes	No
Langfield et al. (2014)	UK	Exposures		Craig and von Peter (2014)		Yes	*Exposures network* = Lending + Marketable Securities + Net CDS Sold + Securities Lending + Repo Exposure + Derivatives Exposure *Funding network* = Lending + Reverse Repo Gross Notional
Molina-Borboa et al. (2015)	Mexico	Exposures	Daily		No power law		Unsecured interbank credit Securities Foreign exchange Derivatives
Montagna and Kok (2013)	Large EU banks	Balance sheet		Hałaj and Kok (2015)			Capital Interbank borrowing (ST,LT) Deposits Interbank loans (ST,LT) Aggregate securities holdings Cash
Soramäki et al. (2007)	US Fedwire	Payment	Daily	Power law (out:2.11, in 2.15)	Yes	2.6	
Veld and van Lelyveld (2014)	Netherlands	Balance sheet	Quarterly	Craig and von Peter (2014) Nested split graph Erdös-Rényi graph[f] Preferential attachment[g]	Yes		No

Table 1: **Empirical Literature on the Topology of the Interbank Network**

[a]Refers to the methodology used to build and/or estimate the network.
[b]The degree of a node is the number of links to other nodes. The degree distribution is the probability distribution of the degree across the nodes.
[c]See section 2.2.1 for a definition.
[d]ST=short term, LT=long term, R=residual of unspecified maturity
[e]OVT=Overnight
[f]In the Erdös-Rényi random graphs, each possible link between any two nodes can occur with a certain independent and identical probability.
[g]See section 4.1.1 for a description of preferential attachment models.

3 Effect of network structure on contagion

This section discusses the theoretical literature on the effect of the network structure on the contagion process.[18] The literature covered in this section is characterized by two features. The first is that it analyzes network dynamics generated by subjecting the network structure to a shock. The second feature is that these dynamics take place on an exogenously given and static network structure.

3.1 Direct linkages

Relevance. In the real world, no bank ever failed because of losses on the interbank market (Upper, 2011). One possibility is therefore that the channel is irrelevant. Several studies[19] have estimated the matrix of bilateral exposures among banks in advanced economies and simulated the extent of contagion following a single bank failure. These studies find little potential for failures resulting from direct interbank linkages. However, these authors assume a fixed structure of interbank claims and use estimation methods[20] that create unrealistically dense networks, and therefore fail to capture all of the dynamics.[21] There are other explanations as to why a default due to losses on the interbank market was never observed. Maybe government interventions have prevented contagion via this channel.[22] Government bail-outs are undesirable for moral-hazard reasons, hence studying how to limit contagion before it occurs is worthwhile. Another argument for studying direct exposures is that the fear of direct contagion on the interbank market can trigger indirect contagion. Models show that the fear of losses in the interbank market may trigger bank runs (Dasgupta, 2004), mark-to-market losses from perceived credit quality deterioration (Glasserman and Young, 2015), confidence crises (May and Arinaminpathy, 2009; Arinaminpathy et al., 2012) or gridlocks (Freixas et al., 2000). It is therefore important to understand the working of the direct channel before exploring its potential effects on other channels of contagion.

Contagion mechanism. Contagion in models of direct linkages is mainly modeled as stemming from the default of a single bank following an idiosyncratic shock to a bank's assets. The bank's default implies that it is unable to repay its interbank liabilities to its

[18] For general results about network structure and contagion, see for example Blume et al. (2011).

[19] Among others, Sheldon and Maurer (1998), Furfine (2003), Upper and Worms (2004), and Wells (2004) estimate the matrix of bilateral exposure among banks for Switzerland, the U.S., Germany and the U.K., respectively. See Upper (2011) for a survey on the results of the network simulation literature.

[20] The most widely used estimation method is maximum entropy, which distributes interbank exposures as evenly as possible among the nodes. Mistrulli (2011) shows that for the Italian banking system the use of maximum entropy techniques underestimates contagion risk relative to an approach that uses information on actual bilateral exposures. See Elsinger et al. (2006) for an exposition of the maximum entropy technique and a discussion. Alternative estimation methods, such as minimum density (Anand et al., 2015), are currently being developed. The best solution would be to have data on bilateral exposures of banks so as to skip the estimation step altogether.

[21] The next section will show that adding indirect linkages via common assets of banks will lead to substantially different simulation results. Notably Cifuentes et al. (2005) show that when the prices of fire sold assets are allowed to change endogenously, the impact of an initial shock may be considerable.

[22] See Laeven and Valencia (2013) for policy responses to banking crises from 1970 to 2011.

counterparties. Since these liabilities are other banks' assets, these banks may now get in trouble, thereby affecting their counterparties. This is how a default cascade starts. This contagion channel works via counterparty risk, where the borrower can not pay back the lender.

3.1.1 Pioneering works: Are more links always better?

Pioneering theoretical works by Allen and Gale (2000) and Freixas et al. (2000) suggest that a highly connected interbank network enhances the resilience of the system to the insolvency of an individual bank. Allen and Gale (2000) set up a network structure involving four regions, with a representative bank in each region. Consumers have the liquidity preferences introduced by Diamond and Dybvig (1983), where consumers have random liquidity needs. Because liquidity preference shocks are imperfectly correlated across regions, banks hold interregional claims on other banks to provide insurance against these shocks. Allen and Gale (2000) demonstrate that the spread of contagion depends crucially on the pattern of interconnectedness between banks. When the network is fully connected (the authors call it 'complete' network) the amount of interbank deposits held by any bank is evenly spread over all other banks. In such a setting, the impact of a shock is dampened since every bank takes a small loss and there is no contagion. By contrast, when the network structure is a ring (each node has one in- and one out-going link, Allen and Gale (2000) call it 'incomplete' network), the system is more fragile, because the initial impact of a shock is concentrated among neighboring banks. Once these default, the early liquidation of long-term assets and the associated loss of value propagate contagion to previously unaffected banks. The possibility of contagion hence depends strongly on the structure of links in the network. The main insight is that the complete claims structure is more robust than the incomplete structure. While the study by Allen and Gale (2000) provides valuable insights into the stability of interbank markets, their model features only four banks and both the network structures employed and the financial structure of banks are too simplistic to be sure that the intuitions generalize to real-world financial systems.

Building on the cross-holdings of deposits as in Allen and Gale (2000), Brusco and Castiglionesi (2007) study the propagation of financial crises among regions in which banks are protected by limited liability and may invest in a highly risky asset. Contrary to the original model, Brusco and Castiglionesi (2007) find that the extent of contagion is greater the larger the number of interbank deposit cross-holdings. A ring network is less conducive to contagion than a complete market structure, which is the opposite result compared to Allen and Gale (2000). What drives these differing results? The crucial transmission channel in Allen and Gale (2000) is the unexpected early liquidation of the long-term asset due to a liquidity preference shock, which may induce bank runs and fire sales, which spread the crisis. Early liquidation is not a relevant mechanism in Brusco and Castiglionesi (2007), since contracts can be written contingent on liquidity preference shocks. The only non-contractible source of contagion is the return on the risky asset. A bank fails if the risky investment fails and therefore financial crises spread directly when a failing bank is unable to pay debts to other banks. Thus, more links between banks increase the probability of contagion.

While in Allen and Gale (2000) there is uncertainty about the timing of deposit withdrawals, in Freixas et al. (2000) there is uncertainty about the location of deposit withdrawals. Interbank connections enhance the resilience of the system to withstand the insolvency of a particular bank, because a proportion of the losses on one bank's portfolio is transferred to other banks through the interbank agreements. Leitner (2005) provides an additional rationale for a highly connected network: more links are desirable because they provide insurance, thereby suggesting that linkages that create the threat of contagion may be optimal. The risk of contagion and the impossibility of formally committing to bail-outs mean that networks develop as an ex ante optimal form of insurance. Agents are willing to bail each other out in order to prevent the breakdown of the entire banking system.

Taken together, the previous studies present mixed evidence for the result by Allen and Gale (2000) and Freixas et al. (2000) that complete networks are more resilient than incomplete ones. Gai and Kapadia (2010) make a crucial point on the relationship between network structure and contagion.[23] They highlight that increased connectivity can simultaneously reduce the probability of contagion but increase its spread conditional on it breaking out. The intuition behind these results is that increased connectivity and risk sharing may lower the probability of contagious default, but conditional on a failure, more connections also allow contagion to spread further. This illustrates the robust-yet-fragile characteristic of financial networks.

Acemoglu et al. (2015a) nuance the debate on connectivity and contagion by differentiating their analysis by the size of the shock. First, they analyze a small shock regime, in which the size of the negative shock is less than the total excess liquidity available to the financial network as a whole. Focusing on regular financial networks[24], Acemoglu et al. (2015a) show that when the magnitude and the number of negative shocks are below this threshold, a more equal distribution of interbank linkages leads to less fragility. In particular, the complete financial network is the configuration least prone to contagious defaults due to more distributed risk sharing. This reflects the findings by Allen and Gale (2000) and Freixas et al. (2000) holds. Second, Acemoglu et al. (2015a) implement a large shock regime, in which the magnitude or the number of negative shocks exceeds the surplus liquidity in the financial system. In this regime, more financial interconnections are no longer a guarantee for stability. Rather, interbank linkages facilitate financial contagion and create a more fragile system. Hence, weakly connected financial networks[25] are significantly less fragile than more complete networks. Such a sharp phase transition can be explained by the fact that with large negative shocks the surplus liquidity of the banking system may no longer be sufficient for absorbing the losses. Therefore, less interbank connections ensure that the losses are shared with the senior creditors of the distressed banks, thereby protecting the rest of

[23] See Amini et al. (2013) for a generalization of their results.

[24] Acemoglu et al. (2015a) define a regular network as one in which the total claims and liabilities of all banks are equal.

[25] Acemoglu et al. (2015a) suggest a network consisting of a collection of pairwise connected banks with only a minimal amount of shared assets and liabilities with the rest of the system.

the interbank network.

3.1.2 Network characteristics and contagion

The research prompted by the works of Allen and Gale (2000) and Freixas et al. (2000) has evolved beyond the trade-off regarding density and resilience. There are more network characteristics that influence contagion than just the level of connectivity. Besides studying network density, Nier et al. (2007) study how the level of capitalisation, the size of interbank exposures and the degree of concentration of the system impact on the likelihood of standard default cascades. Using simulation experiments in random graphs, they find that the effect of the degree of connectivity is non-monotonic. More precisely, a small initial increase in connectivity increases the contagion effect. However, after a certain threshold value, connectivity improves the ability of a banking system to absorb shocks. In addition, they find that the better capitalised banks are, the more resilient is the banking system against contagious defaults. Furthermore, the size of interbank liabilities tends to increase the risk of default cascades, even if banks hold capital against such exposures. Finally, more concentrated banking systems[26] are shown to be prone to larger systemic risk, all else equal. Georg (2013) generalizes the result of Nier et al. (2007) regarding the non-monotonic relationship between connectivity and financial stability to a dynamic setting. In Georg (2013), banks face a stochastic supply of household deposits and stochastic returns from risky investments. This gives rise to liquidity fluctuations and initiates the dynamic formation of an interbank loan network. He compares the stability of different network structures (random, small-world and core-periphery) in normal times and in times of crisis. Times of crisis are characterized by potentially larger losses on risky investments. In times of crisis, core-periphery networks prove to be more stable than purely random networks. In normal times, however, he shows that different interbank network structures do not have a substantial effect on financial stability. In summary, the model financial system exhibits a regime switching property. In normal times, liquidity demand driven interbank lending is low and default cascades are thus contained. In times of crisis, however, individual banks face larger liquidity fluctuations and engage in higher liquidity-driven interbank lending, thereby driving the entire banking system into a contagion-prone regime.

3.1.3 Beyond standard default cascades

In network models with direct linkages, the standard contagion mechanism is the default cascade. Gai et al. (2011) introduce a different contagion mechanism based on liquidity hoarding. With liquidity hoarding, contagion runs the opposite way from the standard default cascade, namely through lending relationships rather than borrowing relationships. After an idiosyncratic haircut shock a bank starts to hoard liquidity and thereby it becomes harder for banks that were previously borrowing from it to comply with their own liquidity requirement without hoarding themselves. As each successive

[26] In this study by Nier et al. (2007), the banking system is becoming more concentrated as the number of banks are decreased while keeping the aggregate size of external assets in the system constant.

bank suffers a liquidity shortfall, its hoarding potentially triggers a liquidity shortage for its own counterparties. So hoarding can potentially cascade through the system. Gai et al. (2011) study how network characteristics influence this particular contagion process. They design a baseline scenario in which the links connecting banks are distributed roughly uniformly (Poisson). They study what happens when a random adverse haircut shock at one bank forces it to start hoarding liquidity. To assess the role of concentration, they study how the results change under a fat-tailed (geometric) network configuration, where some banks in the network are much more highly connected than the typical bank. This leads to a tiered structure. Contagion is less severe and less likely for low average degrees than under the Poisson distribution.[27] Gai et al. (2011) also explore the differing consequences of a targeted shock which affects the most interconnected interbank lender under both network configurations. Contagion occurs more frequently under both distributions, but for the less concentrated network, it makes only a small difference. For the concentrated network it makes contagion quasi-certain for a very wide range of average degrees. What drives this result is that the most connected bank under a Poisson distribution is not much more connected than the average bank, whereas under the fat-tailed distribution the most connected bank is connected to a large part of the network.[28]

The cross-holding model of Elliott et al. (2014) features two main departures from the standard financial network model with direct links and default cascades. First, the network is constituted of equity cross-holdings and not interbank exposures. Second, the model includes bankruptcy costs, which become an important element in the contagion mechanism. From the initial cross-holdings matrix Elliott et al. (2014) are able to derive a formula which shows how the value of each organization depends on the values of the assets which the organizations in the financial network hold and on failure costs. It is therefore possible to track how asset values and failure costs propagate through the network. Due to the cross-holdings, the organizations loose value if the value of an asset drops, but if this asset drop causes one of them to fail, these failure costs also affect the companies holding part of the failing company. If these companies also fail in the second round of the cascade, the cumulative failure costs increase again for the rest of the system. This accumulation of failure costs can exceed the drop in asset value that precipitated the cascade and thereby amplify the propagation of shocks. The probability and the magnitude of these cascades depends on two characteristics of the cross-holdings. The first aspect is integration, which refers to the level of exposure of organizations to each other. Increasing integration leads to an increase in exposures which tends to increase the probability and magnitude of contagion. The second characteristic is diversification which refers to how spread out cross-holdings are. Depending on the level of diversification, a failure of one organization can have very different effects. In the case of low diversification, some organization can be very dependent on the stability of

[27]This reflects the well-known result by Albert et al. (2000) that fat-tailed networks tend to be more robust to random shocks.

[28]This reflects another result by Albert et al. (2000) that fat-tailed networks are vulnerable to targeted attacks on key nodes.

others, but the low density of the network limits propagation. For an intermediary level of diversification, the network is dense enough for cascades to occur, but at the same time cross-holdings are still large, so that an individual failure leads to far-reaching cascades. When diversification is high, organizations become insensitive to another organization's failure. In summary, Elliott et al. (2014) show that an economy is particularly vulnerable to cascades when both integration and diversification are at intermediate levels, since connections exist to propagate shocks and organizations hold enough shares of others for these drops in value to matter.

Dasgupta (2004) introduces informational contagion in an interbank network. He shows that linkages between banks in the form of deposit cross-holdings can be a source of contagion when the arrival of negative information leads to coordination problems among depositors and widespread runs.

Finally, Cohen-Cole et al. (2015) depart from the concept of contagion as a default cascade. They model systemic risk in the interbank network as the propagation of incentives or strategic behavior rather than the propagation of losses after default. They explain bank profitability based on competition incentives and the outcome of a strategic game. As competitors' lending decisions change, banks adjust their own decisions as a result, thereby generating a transmission of shocks through the system. More specifically, they illustrate how small changes in uncertainty, risk, or behavior propagates through the network and leads to changes in volumes and prices.

3.2 Indirect linkages

Relevance. Indirect connections in financial networks include for example common assets (Greenwood et al., 2015), overlapping portfolios (Caccioli et al., 2014) and linked portfolio returns (Lagunoff and Schreft, 2001).

Contagion mechanism. Propagation of shocks is mainly driven by fire sales. When a bank experiences a negative shock to its equity, a natural way to return to target leverage is to sell assets. If the asset is illiquid, then asset sales depress prices, in which case one bank's sales impact other banks with common exposures to this asset.

Greenwood et al. (2015) present a model in which fire sales of a common asset propagate shocks across an interbank network. They anaylze how fire sale spillovers add up across banks and how susceptible individual banks are to episodes of deleveraging by others. In the model, a link between banks is established when they are both exposed to large amounts of the same asset. When a highly connected bank sells assets, a classic fire sales mechanism is triggered. Greenwood et al. (2015) show that the banking system is more susceptible to contagion when asset classes that are large in dollar terms are also held by the most levered banks. In order to reduce fire sale spillovers, assets that are both volatile and illiquid should be dispersed across banks, as the same shocks will generate less price impact in a deleveraging cycle.

Caccioli et al. (2014) analyze fire sales as a contagion mechanism between leveraged financial institutions with overlapping portfolios.[29] Compared to Greenwood et al.

[29]For another model of indirect linkages, see Lagunoff and Schreft (2001). As in Caccioli et al. (2014),

(2015), they consider a financial system where banks invest in multiple assets. Whenever a bank invests in an asset, they draw a link in the network connecting that bank to that asset. The resulting network is bipartite, meaning that there are two groups of nodes (banks and assets) and that there are links only between these two groups. As the diversification of the banks' portfolios increases, they find that the system undergoes two phase transitions. Below the first transition, the interbank network is too sparse for shocks to propagate. Between the two transitions, banks are both vulnerable to shocks in their asset prices and connected enough for these shocks to propagate. Above the second transition, banks are robust to devaluations in a few of their assets.

3.3 Interactions between direct and indirect linkages

Relevance. The vast majority of empirical financial network simulation studies find little potential for failures resulting from direct interbank linkages.[30] Banks have however many more types of links than just direct interbank exposures. Indirect links between banks exist for example when the portfolios of financial institutions overlap due to investment in common assets. The literature reviewed in this section combines direct and indirect links in an interbank network. Combining these features not only shows how shocks are propagated, but is also able to capture how shocks are amplified.

Contagion mechanism. Contagion is driven both by default cascades and by fire sales. From a risk perspective, these models interact counterparty risk resulting from direct exposures with liquidity risk resulting from the fire sales channel.

3.3.1 Models incorporating the fire sales mechanism by Cifuentes et al. (2005)

Cifuentes et al. (2005) build a theoretical model of an interbank network and combine direct linkages with indirect linkages via overlapping asset portfolios of banks. The key finding is that when one allows for endogenous changes in the prices of fire sold assets, initial shocks may be amplified in the interbank network. After an idiosyncratic shock, one bank in the network fails and its remaining assets are sold on the market. When the market's demand for illiquid assets is inelastic, fire sales depress the market prices of such assets. In a mark-to-market regime, the update of the asset prices can induce a further round of endogenously generated sales of assets, depressing prices further and inducing further sales. In this simple setup, Cifuentes et al. (2005) are able to show that small shocks can amplify contagion.[31]

Both Nier et al. (2007) and Gai and Kapadia (2010) extend their model of direct exposures with the fire sales model by Cifuentes et al. (2005). Gai and Kapadia (2010)

---

agents hold portfolios of assets, but in Lagunoff and Schreft (2001) the portfolios are linked in the sense that the return of an agent's portfolio depends on the portfolio allocations of other agents.

[30] See Upper (2011) and Summer (2013) for a survey on the results of this literature.

[31] In the macro-finance literature, endogenous asset price changes due to fire sales are also an important modeling device to generate the amplification of initially small negative shocks. See section two of the survey by Brunnermeier et al. (2013).

find that adding an indirect channel does not alter the robust-yet-fragile property of the original network. Nier et al. (2007) find that liquidity risk increases default cascades for any level of connectivity. Furthermore, they find that illiquid asset holdings make concentrated banking systems especially fragile. In a concentrated system, the default of a large bank requires the liquidation of a large amount of assets. This exacerbates asset price contagion for concentrated systems compared to less concentrated systems. Caccioli et al. (2015) also show the importance of considering both counterparty and liquidity risk by simulating shocks in an interbank network using Austrian data on direct exposures. The system is rather stable after the failure of a single bank if counterparty risk is the only contagion mechanism. Then, they add a theoretical model of indirect interbank linkages based on Cifuentes et al. (2005), where they connect all banks in the network to a unique common asset. Combining counterparty risk with overlapping portfolio risk, contagion is strongly amplified, resulting in much larger cascading failures than would be observed otherwise.[32]

3.3.2 Other models with direct and indirect links

Glasserman and Young (2015) estimate the extent to which defaults and losses are magnified by the interbank network over and above the original shocks to asset values. Restricting the focus on direct linkages, they compute the probability that default at one bank leads to defaults at other banks via network spillovers. Then, the resulting probability is compared with the probability that all of these banks default by direct shocks to their outside assets. They find that losses due to network spillovers are small under a wide range of shock distributions. Like Cifuentes et al. (2005), Glasserman and Young (2015) also explore the effect of a mark-to-market regime on financial stability. The main difference in their setup is that assets do not need to be fire sold to disrupt financial stability. Glasserman and Young (2015) incorporate confidence crises where the bank's perceived ability to pay declines, causing the market value of its liabilities to fall.[33] In a mark-to-market regime this reduction in value can spread to other banks who also hold these liabilities among their assets. This channel of contagion is found to be considerably more important than direct spillover effects.

Caballero and Simsek (2013) analyze the impact of complexity in the financial system on financial stability. Banks only know their own direct exposures, but there is increasing uncertainty about exposures of banks that are further away in the network. During normal times, it is sufficient for banks to understand the financial situation of their direct counterparties. In uncertain times however, when a surprise liquidity shock hits parts of the network, the possibility of default cascades arises, and banks become concerned that they might be indirectly hit. Banks now need to have more than only local knowledge, they also need to understand the financial situation of the counterparties to which they

[32]This confirms results of more traditional macro finance models by Geanakoplos (2010) and Brunnermeier and Pedersen (2009) that market liquidity and funding liquidity are mutually reinforcing and their interaction can lead to liquidity spirals.

[33]For the impact of confidence on contagion in interbank networks, see also May and Arinaminpathy (2009) and Arinaminpathy et al. (2012).

are indirectly linked (via other counterparties). Uncertainty about counterparty risk leads banks to hoard liquidity. This structure exhibits strong interactions with secondary markets for banks' assets. Banks in distress can sell their assets to meet the surprise liquidity shock. If the shock is small, buyers rule out an indirect hit and absorb the fire sold assets. If the shock is large, banks start hoarding liquidity as a precautionary measure and buyers turn into sellers, exacerbating the fire sales.

Anand et al. (2013) push the analysis of interactions further by combining three sets of agents: domestic banks, overseas banks and firms.[34] The model is then calibrated to advanced country banking sector data. The model highlights how adverse credit shocks are propagated through the direct exposures amongst - and between - domestic banks and overseas banks. It also shows how default cascades are amplified by asset fire sales and lending is curtailed in the macroeconomy as credit crunch effects take hold.

[34]For a network formation model of a corporate lending network with banks and non-financial corporations, see Halaj et al. (2015).

Paper	Links	Initial shock	Loss propagation	Formation	Structure	Bank #
Aldasoro et al. (2015)	D: interbank market I: common asset	shock to non-liquid asset	default cascade, fire sales, liquidity hoarding	endogenous	core-periphery	N
Aldasoro and Faia (2015)	D: interbank market I: common asset	shock to non-liquid asset	default cascade, fire sales, liquidity hoarding, bank run	endogenous	core-periphery	N
Acemoglu et al. (2015a)	D: interbank market	idiosyncratic shock to asset returns	default cascade	exogenous	complete, ring	N
Allen and Gale (2000)	D: cross-holdings of deposits	liquidity preference shock	bank run, fire sale	exogenous	complete, ring, two by two	4
Allen et al. (2012)	I: common assets	news shock (about bank solvency)	failure to rollover debt, defaults	strategic	ring, clustered	6
Anand et al. (2012)	D: interbank market	news shock	failure to rollover debt, defaults	strategic		N
Battiston et al. (2012b)	D: credit network	shock to equity level	default cascade	exogenous	connected	N
Bräuning et al. (2015)	D: interbank market	credit risk uncertainty	drying up of interbank market	endogenous		50
Bluhm et al. (2014b)	D: interbank market I: common asset	shock to asset	default cascade, fire sales	endogenous		N
Brusco and Castiglionesi (2007)	D: cross-holdings of deposits	liquidity shocks	default cascade	exogenous	complete, ring	2, 4
Caccioli et al. (2015)	D: interbank market I: common asset	shock to common asset	interbank defaults, fire sales	data	core-periphery	830
Caccioli et al. (2014)	I: common asset	bank failure	fire sales	random	bipartite (assets and banks)	N
Cifuentes et al. (2005)	D: interbank market I: common asset	failure of one bank	fire sales with mark to market	exogenous	from empty to complete	10
Dasgupta (2004)	D: cross-holdings of deposits	regional liquidity shock	failure of debtor bank	exogenous	complete	2
Elliott et al. (2014)	D: cross-holdings of shares	idiosyncratic shock to asset	default cascade	random	random	N
Fique and Page (2013)	D: interbank market	news shock	failure to rollover debt, defaults	strategic		N
Freixas et al. (2000)	D: interbank market	solvency shock	bank run, fire sale	exogenous	complete, ring	N
Gai and Kapadia (2010)	D: interbank market I: common asset	idiosyncratic shock to asset	interbank defaults, fire sales	random		N
Gai et al. (2011)	D: interbank market	funding liquidity (haircut) shock	liquidity hoarding	random	random	250
Georg (2013)	D: interbank market	deposit withdrawals, loss on investment common shock to capital	default cascade	endogenous	random, scale-free, small-world	100
Glasserman and Young (2015)	D: interbank market I: common asset	shock to asset value	default cascade	exogenous		N
Hałaj and Kok (2015)	D: interbank market	shock to bank capital	default cascade	endogenous		80
Lagunoff and Schreft (2001)	I: common asset	failure of investment	investment failures	strategic	chain	N
Leitner (2005)	D: interbank market	liquidity shock	default cascade	exogenous	complete, no links	N
Lenzu and Tedeschi (2012)	D: interbank market	liquidity shock	default cascade	random	scale-free	150
Lux (2014)	D: interbank market	liquidity shock	no contagion	random	core-periphery	50, 250
Nier et al. (2007)	D: interbank market I: common asset	idiosyncratic shock to asset	default cascade	random	random, tiered	25
Vivier-Lirimont (2006)	D: interbank market	liquidity shock	default cascade, fire sale	exogenous	star, ring, complete	N

Table 2: **Theoretical Interbank Network Literature** (D=direct, I=indirect)

4 Network formation

One limitation of static models of financial networks, is that they do not provide an account of link formation, that is, they do not model the dynamic process by which financial institutions enter into obligations to one another in the first place. This challenge has been taken up recently in the financial networks literature.[35]

Three main ways to model network formation have crystallized in the interbank networks literature. One branch of the literature builds on random link formation, for example using network growth models. Typically, these are random network models where new nodes are born over time and form attachments to existing nodes when they are born.[36] In the financial networks literature, an empty network[37] is given and nodes are then connected in a mechanical way. One option is to generate links according to a stochastic process (Anand et al., 2012). Another option is to condition random link formation on characteristics of the nodes, making it more likely to create links with banks that have higher profits (Lenzu and Tedeschi, 2012) or a higher willingness to extend an interbank loan (Lux, 2014). This process of network formation is called preferential attachment. Trust is an important element in this regard. Banks trust other banks based on their performance or their reliability in lending. An additional feature of preferential attachment is that it provides a mechanism to generate scale-free distributions (Barabási and Albert, 1999), which is also a feature of the interbank network.

A second area uses strategic network formation[38], where banks assess the costs and benefits from forming a link with another bank. A prominent theme in strategic network formation are rollover decisions by banks, often modeled using global games techniques. Creditors strategically decide to rollover a loan after receiving a signal about the solvency or performance of the borrower (Allen et al., 2012; Fique and Page, 2013; Anand et al., 2012). Also using strategic network formation, Farboodi (2014) and In't Veld et al. (2014) analyze how bank heterogeneity can lead to the formation of a core-periphery network. Further, Acemoglu et al. (2015b) show how banks may overconnect and underdiversify in equilibrium, potentially creating networks that are excessively prone to contagious defaults.

The third area builds network formation on the basis of portfolio optimization by financial institutions. Two approaches can be distinguished. The first is where banks choose the amount of interbank lending and/or borrowing by optimizing their (heterogeneous) balance sheets (Aldasoro et al., 2015; Bluhm et al., 2014a,b). This optimal amount then gets allocated among the banks. A second option is to fix the overall amount of borrowing and lending (Bräuning et al., 2015; Hałaj and Kok, 2015). Banks then have the choice of their counterparty.

[35] See Jackson (2005) for a survey of network formation models in economics.

[36] For an introduction to the modeling of network growth models, see the textbook by Jackson (2010).

[37] In an empty network there are no links between the nodes.

[38] For an introduction to the modeling of strategic network formation, see the textbook by Jackson (2010).

4.1 Relationship lending and random network formation

Preferential lending or relationship lending in the interbank market is empirically relevant.[39] Models with exogenously given network structures have already shown the importance of confidence crises in driving contagion (Arinaminpathy et al., 2012; Glasserman and Young, 2015; May and Arinaminpathy, 2009). It turns out that trust is also a key driver in the formation of interbank relations.

Lenzu and Tedeschi (2012) implement link formation via a preferential attachment rule[40], according to which each bank can enter into a lending agreement with other banks with a probability proportional to its profit.[41] The key element in the model is the trust parameter. It captures how much banks trust the information about other banks' profits. Variations in the trust parameter lead to the formation of very different network structures, ranging from random to scale-free. When trust is strong, a core-periphery structure emerges. In the dynamic model of the interbank market by Lux (2014), trust between banks is also crucial in driving the emergence of a core-periphery structure. Links form according to a simple reinforcement-learning scheme. If a bank has successfully obtained credit from another bank, the borrower is more likely to contact this creditor again. If credit was not granted, trust in this potential borrower will decline. The dynamic evolution of the interbank market leads to the emergence of a core-periphery structure. Introducing another variation of trust in interbank networks, Iori et al. (2015) build a model of interbank trading with memory, where memory is used as a proxy for trust in the model. The basic assumption is that a lender who was engaged in a lending relationship with a borrower in the past will be more likely to lend to that borrower again in the future compared to unknown borrowers. In this setup, a stronger memory parameter leads to increasingly stable trading relationships. The model is able to reproduce the characteristics of preferential lending empirically observed in the e-MID market.

4.2 Strategic network formation and rollover risk

Anand et al. (2012) want to understand how funding maturity and network structure interact to generate systemic financial crises. They combine a dynamic model of network growth with strategic elements. Links are created using a random matching framework. The formation of a debt contract between any two banks is a random draw from all possible contracts between banks in the network. The evolution of the interbank network is governed by three Poisson processes representing link addition, link decay and the arrival of adverse signals. The strategic element lies in the rollover decision of the

[39]See for example the empirical studies on relationship lending in the German (Bräuning and Fecht, 2012), Portuguese (Cocco et al., 2009) and Italian (Affinito, 2012) interbank markets.

[40]The network formation used here is based on Barabási and Albert (1999), who develop a method to generate power-law networks based on two features: (i) networks expand continuously by the addition of new nodes, and (ii) new nodes attach preferentially to nodes that are already well connected (called a preferential attachment rule).

[41]This is also called a fitness mechanism, because link formation is based on the bank's performance. See also Montagna and Lux (2013) for a network formation model based on a fitness algorithm.

bank's creditors, modeled as a global game. Creditors receive information about the bank's future profits and then decide to withdraw the funds or to roll over to maturity. The model shows how the arrival of bad news about a financial institution can lead others to lose confidence in it and how this propagates through the interbank market. Anand et al. (2012) are able to compute endogenous default rates depending on the cost of miscoordination of the creditors and mean assets and liabilities. The banking system exhibits tipping-points and hysteresis. If the system tips into a bad state, the crisis is persistent and a more favorable environment is required to start the interbank market's normal functioning again. Generalizing these results, Fique and Page (2013) show that even without coordination failures, tipping points can occur depending on the importance of the network as an information propagation mechanism. They model banks' rollover decisions within a network formation game. Lenders receive a private signal, update their prior beliefs and decide whether or not to rollover the loan. The rollover decision by a lender is a signal about the creditworthiness of the borrower and through these signals information propagates through the interbank network.

Allen et al. (2012) show how different asset structures affect the rollover risk resulting from short term finance. There are six banks and each bank can swap shares of its own investment project with other banks. There is a due diligence cost associated with the exchange of projects. In equilibrium, banks have to trade off the advantages of diversification with the due diligence costs. The equilibrium concept used is one of a pairwise stable network.[42] Two possible asset structures can arise. In a ring network of six banks, defaults are more dispersed. When banks form two clusters of three banks each, groups of banks hold common asset portfolios and default together. Creditors receive aggregate signals about bank solvency and then decide to rollover debt. In the presence of short-term debt, creditors refuse to roll over in response to adverse signals. Consequently, all banks are inefficiently liquidated. This information contagion is more likely when banks form clusters. In the presence of long-term debt, welfare is the same under both asset structures.

4.3 Strategic network formation and excessive counterparty risk

Farboodi (2014) builds a model of strategic network formation leading banks to overconnect in equilibrium and therefore generating excessive counterparty risk. Some banks in the model have access to a risky investment opportunity while other banks do not. In order to invest, banks need to raise resources either from households, to which banks have random access, or from other banks. The unequal access to investment opportunities and resources leads to endogenous interbank intermediation. Each bank chooses its interbank relationships to get the highest expected possible rate on the funding it lends out and the investment it undertakes. There are two forces at play in the formation of the equilibrium network. First, with positive intermediation rents, competition implies

[42] According to Jackson and Wolinsky (1996), a network is pairwise stable i) if a link between two individuals is absent from the network then it cannot be that both individuals would benefit from forming the link, and ii) if a link between two individuals is present in a network then it cannot be that either individual would strictly benefit from deleting that link.

that in equilibrium the banks who are able to offer the highest expected returns become intermediaries (i.e. borrowers and lenders at the same time). These are the banks who have access to the risky investment technology. Second, the other banks still want to earn the highest possible returns. Therefore, these banks opt for the shortest connecting path to investing banks, so that they avoid paying intermediation spreads as often as possible. These two dynamics lead to the formation of a core-periphery equilibrium network in which a subset of banks with risky investment opportunities constitutes the core.[43] The network is inefficient relative to a constrained efficient benchmark since, on the one hand, banks who make risky investments overconnect and expose themselves to excessive counterparty risk, while, on the other hand, banks who mainly provide funding end up with too few connections. In a closely related paper, Acemoglu et al. (2015b) also find that banks expose themselves to excessive counterparty risk. Though both papers consider the endogenous formation of financial linkages, one of the main differences[44] is that in Farboodi (2014) the face value of the contracts and the allocation rule of intermediation rents are fixed exogenously. In comparison, in Acemoglu et al. (2015b) all interbank interest rates are determined endogenously. The key assumption is that banks lend to one another through debt contracts with contingency covenants. These allow lenders to charge different interest rates depending on the risk-taking behavior of the borrower. As a first result, it is shown that due to the contingency covenants, all bilateral externalities are internalized, implying that each bank takes the impact of its actions on its direct counterparties into account. For an economy consisting of three banks (i.e. where banks are only exposed to bilateral counterparties), Acemoglu et al. (2015b) show that the endogenous adjustment of the interbank interest rates ensures that the extent of interbank lending in equilibrium coincides with the constrained efficiency benchmark. As a second result, it is shown that in the presence of counterparty risk beyond bilateral exposures, the efficiency result may no longer hold. Indeed, as long as banks cannot write contracts that are contingent on the complex details of the interbank network, the networks that are formed in equilibrium may not be socially efficient. While banks take the effects of their actions on their direct counterparties into account, they fail to internalize the externalities that they impose on the rest of the financial system (beyond their direct counterparties) and therefore may overlend in equilibrium. In this setup, financial stability can be improved and the social surplus can be increased if some banks refrain from lending.

Eisert and Eufinger (2014) explain why it can be beneficial for banks to be highly interconnected via direct and indirect linkages, thereby paving the way for excessive exposures. First, banks have an incentive to artificially channel funds through the interbank market, because they can significantly increase the expected repayment of unin-

[43] The estimation of the structural dynamic network model by Bräuning et al. (2015) confirms the finding that part of the tiered network structure can be explained by banks in the core having a structural liquidity deficit (i.e. an investment opportunity) and peripheral banks typically having a structural funding surplus.

[44] Another important difference is that Acemoglu et al. (2015b) does not provide predictions on the overall structure of the financial network since banks in the model are located on a ring. Farboodi (2014) allows more general network structures to form endogenously.

sured creditors if their funds travel through the interbank market before being invested in loan portfolios. The expected repayment increases in such a situation because the funds of the uninsured creditors are then covered by the banks' implicit government guarantees. Second, given this incentive to become highly interconnected exists, Eisert and Eufinger (2014) show that banks can maximize the government subsidy per invested unit of capital by having correlated portfolios and thereby creating indirect linkages. If banks invest in uncorrelated assets, they are not always successful in the same states. In such a setup, a successful bank may fail due to a default cascade originating from an unsuccessful bank. When banks invest in correlated assets, banks default together and contagion can not occur. This increases the expected residual bank profits compared to the case where the banks invest in uncorrelated assets. In summary, the incentive structure leads to high systemic risk on the asset side (correlated portfolios) and on the liability side (many direct interbank exposures).

4.4 Network formation via portfolio optimization

Bluhm et al. (2014b) include the fire sales model of Cifuentes et al. (2005) into a model with endogenous network formation. Bluhm et al. (2014b) construct a dynamic network model with risk neutral, heterogeneous and micro-founded banks. Banks are heterogeneous in the sense that they hold different amounts of equity capital and differ for the returns on non-liquid assets. Banks solve an optimal portfolio problem, taking into account liquidity and capital constraints. Links emerge endogenously from the interaction of intermediaries' borrowing and lending decisions and an iterative tâtonnement process which determines market prices endogenously. Contagion is made possible through the direct channel via default cascades and through the indirect channel via fire sales. Aldasoro et al. (2015) extend this model by including risk averse banks. This creates an additional channel of contagion: liquidity hoarding due to risk aversion. The resulting network configuration is able to match key characteristics of empirical interbank networks: it exhibits a core-periphery structure, dis-assortative behavior and a low clustering coefficient. Aldasoro and Faia (2015) further include a fourth contagion channel via bank runs. In this extension of the previous model, liquidity is scarce for two reasons. The first is that banks are risk averse, hence in the face of shocks they tend to hoard liquidity. Second, banks have to raise short term funding from external investors, who assess the quality of their investment based on signals about banks' returns. Adverse signals about a bank's performance leads investors to run the bank. In summary, banks can experience liquidity shortages due to liquidity hoarding and banks runs. The networks emerging from the above models are used to simulate macroprudential policies.[45] Abstracting from the possible impact of fire sales of assets considered above but including the possibility of rollover risk, Hałaj and Kok (2015) also model credit interlinkages resulting from portfolio optimization and endogenous price mechanisms. Hałaj and Kok (2015) take a sample of 80 large EU banks. Based on their balance sheet composition, banks optimize their interbank assets taking into account risk and regulatory

[45]See section 5.4 for details.

constraints as well as the demand for interbank funding, which results in a preferred interbank portfolio allocation for each bank in the system. The supply and demand for interbank lending is determined in a bargaining game where banks are allowed to marginally deviate from their optimal interbank allocations and the prices they offer on those. This sequential optimization process is repeated in an iterative manner until a full allocation of interbank assets is achieved. The emerging network is then used for policy simulations.[46]

In a novel and distinct approach, Bräuning et al. (2015) introduce and estimate a structural dynamic network model of the formation of lending relationships in the unsecured interbank market. Each bank faces the dynamic problem of allocating resources to monitoring counterparties to reduce credit risk uncertainty and choosing which bank to transact with to maximize expected discounted payoffs. In order to smooth random liquidity shocks, banks can bilaterally Nash bargain with potential counterparties about loan conditions.[47] Bräuning et al. (2015) estimate the structural model parameters by indirect inference using network statistics of the Dutch interbank market. The estimated model provides an accurate explanation of the low density and stability of the lending network. Peer monitoring and credit risk uncertainty are key drivers of the emergence of stable interbank lending relationships.

5 Policy insights from interbank networks

Representing the banking system as a network is arguably more realistic than to model it as a representative bank, as traditional macro finance models do. For this reason, the network literature can be a useful source for policy insights on financial stability. Not just recently have financial stability experts at central banks, supervisory authorities and international financial organizations become interested in the policy applications of network analysis. For example, the Bank of England's chief economist Andrew Haldane has been an early promoter of the network approach to financial systems (Haldane, 2009; Haldane and May, 2011; Gai et al., 2011). The European Central Bank held already in 2009 a workshop on 'Recent advances in modeling systemic risk using network analysis'.[48] The IMF has recently reviewed tools used to identify and measure interconnectedness in the context of prudential policy (Arregui et al., 2013).[49] The following sections provide a brief overview of the literature on network measures for identifying critical institutions, along with a discussion of stress testing using network models and of policy insights for monetary and macro-prudential policy.

[46] See section 5.4 for details.

[47] Bräuning et al. (2015) characterize the bilateral equilibrium interest rate as an increasing function of the outside option for borrowing and lending (given by the central bank's standing facilities), counterparty risk uncertainty and the lender's market power relative to the borrower.

[48] The detailed summary of the workshop can be found here `http://www.ecb.europa.eu/pub/pdf/other/modellingsystemicrisk012010en.pdf`.

[49] See also the IMF study by Chan-Lau et al. (2009) for a comparison of the network approach with other methods to assess direct and indirect financial interconnectedness.

5.1 Identifying critical institutions

Identifying critical financial institutions is important for policy-makers.[50] There is a growing awareness that not only the size of an institution matters, but also its interconnectedness. Network concepts can be very useful to assess both interconnectedness and key banks in the financial system (Arregui et al., 2013). Two measures stand out in this regard. The first one is centrality (Borgatti, 2005). Centrality measures infer from the pattern of linkages among financial institutions the extent to which a node is 'central' in the financial network. The second measure is clustering, which separates the network into subgroups ('clusters') of nodes that have closer connections to each other than with those outside the cluster. It can help identify subgroups of nodes with close connections and 'gatekeeper' institutions or systems that bridge across different clusters allowing for the contagion to spread out.[51]

Langfield and Soramäki (2014) provide an in-depth overview of the network literature on identifying systemically important banks. Measures to identify critical institutions include 'DebtRank' (Battiston et al., 2012c), SinkRank (Soramäki and Cook, 2013) or measures based on input-output analysis for singlelayer (Aldasoro and Angeloni, 2015) and multilayer networks (Aldasoro and Alves, 2015). A general overview of systemic risk measures is provided by Bisias et al. (2012).

5.2 Stress testing

Central banks, supervisory authorities and policy institutions such as the IMF are currently developing tools for stress testing the banking sector using network models (Anand et al., 2014; Canedo and Jaramillo, 2009; Chan-Lau et al., 2009; Espinosa-Vega and Solé, 2014; Hałaj and Kok, 2015). According to the definition of the Basel Committee on Banking Supervision, stress testing is a tool used by authorities to quantify the impacts that large but plausible negative shocks could have on the capital positions of banks.

Supervisory authorities can apply network analysis to identify systemic and vulnerable institutions, as well as for tracking potential contagion paths. Espinosa-Vega and Solé (2014) suggest that network analysis could be combined with regular stress testing exercises in order to gain a more comprehensive picture of fragility in a given banking system. This could be done in two ways. The first option is to run traditional stress tests to identify the types of shocks that could have the largest first-round effects on individual institutions. Once these shocks are determined, they could be fed into a network model to assess their further impact in additional rounds of contagion. The second option is to begin with network analysis and to apply a first set of shocks to the financial system in order to identify systemic institutions and then perform a more detailed stress test of these institutions. Espinosa-Vega and Solé (2014) also highlight the challenges ahead. They emphasize that it is still very difficult to obtain comprehensive bank-level

[50] See for example the methodology to identify systemically relevant banks by the Basel Committee on Banking Supervision (2013).

[51] See for example ECB (2006) for an application of cluster analysis to identify systemically relevant banks.

data. Some of the areas where better data are needed include information on banks' exposures and funding positions, with breakdowns by counterparty, currency, and remaining maturity. Additional data on off-balance-sheet and shadow banking activities would also make stress testing more informative. Chan-Lau et al. (2009) also discuss the importance of filling existing information gaps on cross-market, cross-currency, and cross-country linkages.

5.3 Insights for monetary policy

The question as to whether and how monetary policy can foster financial stability has always played an important role in the macro finance literature, but the recent global financial crisis has clearly provided a new impetus for research. In macro models this question has typically been answered by analyzing whether targeting financial variables in operational monetary policy rules can smooth the volatility of asset prices and other financial variables. But this modeling framework neglects the diffusion of risk through fire sale spirals and direct interconnections within the banking system. These network features are crucial characteristics of the interbank market, where monetary policy implementation takes place through the supply of liquidity and interest rate expectations. As Bluhm et al. (2014b) highlight, central bank interventions can affect market liquidity as well as systemic risk. On the one side, increased liquidity allows banks to be resilient to adverse shocks. On the other side, an implicit monetary policy guarantee can generate moral hazard and lead to higher risk taking. This carries an externality, increasing the likelihood of adverse shock transmission to the overall banking system as well as the real economy.

Central banks are introduced into the interbank network by allowing one bank either to supply an unlimited amount of liquidity (Bluhm et al., 2014b) or to provide liquidity against eligible collateral (Georg, 2013). Bluhm et al. (2014b) analyze the effect of monetary policy on financial stability using an interbank network with endogenous link formation. Systemic risk is measured by the overall probability of the system to default. A financial crisis arises in the form of default cascades and fire sale spirals as modeled in Cifuentes et al. (2005). The central bank injects or withdraws liquidity on the interbank markets to achieve its desired interest rate target. On the one hand, this has beneficial effects in the form of stabilized interest rates and increased loan volume. On the other hand, central bank liquidity has detrimental effects, because it leads to higher risk taking incentives. In this setup, the central bank's supply of liquidity generally increases systemic risk. Georg (2013), however, shows that the central bank can stabilize the financial system in the short run in a model of the interbank market where banks are subject to stochastic returns on investment and a random supply of deposits. Central bank liquidity provision helps banks to withstand liquidity shocks for a longer time, but also allows otherwise insolvent banks to survive. The introduction of a common shock to the capital of all banks leads to widespread financial instability but is less damaging for the liquidity provision of the interbank market. In summary, interbank contagion mainly requires liquidity provision, while a common shock requires banks to be recapitalized.

5.4 Insights for macro-prudential policy

The cornerstone of the current international regulatory agenda is the setting of higher requirements for banks' capital and liquid assets. The traditional rationale for such requirements is that they reduce idiosyncratic risks to the balance sheets of individual banks. According to Haldane and May (2011), an alternative and more far-reaching interpretation is that they are a means of strengthening the financial system as a whole by limiting the potential for network spillovers. The theoretical network literature has done policy experiments to simulate the impact of different regulatory measures on systemic risk. The main regulatory measures analyzed are liquidity requirements, limits to counterparty credit risk using large exposure limits and credit valuation adjustments as well as capital requirements.

5.4.1 Liquidity requirements

Liquidity requirements is the minimum ratio of banks' liquid assets to their short-term liabilities that banks have to observe. Haldane and May (2011) argue that liquidity ratios can prevent systemic liquidity spillovers arising from fire sales or liquidity hoarding. Gai et al. (2011) simulate the effect of an introduction of two types of liquidity requirements in an interbank network. The first liquidity requirement is a uniform increase in liquid asset holdings. The authors find that imposing such a uniform liquidity requirement improves the resilience of the financial system. The second liquidity requirement imposes an increase in liquid assets that is positively related to banks' interbank assets. To make both simulations comparable, the average increase in liquid assets is identical in both policy exercises. The liquidity requirement targeting large banks is more effective in reducing the probability and spread of contagion than an equivalent across-the-board increase in liquidity requirements.

Aldasoro et al. (2015) also simulate the effect of changing liquidity requirements in an interbank network featuring contagion via default cascades, fire sales and liquidity hoarding. They find that increasing the liquidity requirement reduces systemic risk and the contribution of each bank to it. As banks must hold more liquidity for precautionary motives, their exposures in the interbank market decline, limiting the scope for network externalities. A higher liquidity requirement leads to a substantial reduction in asset holdings. This can be seen as beneficial, since it restricts the scope for pecuniary externalities. But there is also a cost associated to this reduction in asset holdings, namely in terms of efficiency of the system. Including in the previous model a contagion channel via bank runs, Aldasoro and Faia (2015) study the effects of phase-in increases of liquidity coverage ratios. The response of systemic risk is increasing in the initial stages and then stays flat. This evolution can be explained as follows. An increase in the coverage ratio forces banks, which borrowed in the interbank market and invested in non-liquid assets, to deleverage and liquidate assets. The price of non-liquid assets declines and thereby inflicts accounting losses on all banks. The drop in value of the banks' assets induces depositors to run the banks. Liquidity becomes even scarcer, triggering further fire sales. The policy experiment analyzed shows that the goal of making the system more resilient turns into an action that renders it more fragile. Aldasoro and Faia (2015) also test an alternative approach where liquidity requirements are increased only for the systemically important banks, while reducing it for the others. The increase in the liquidity requirement for large banks leads to an initial fall in the value of their assets, but it also reduces their direct and indirect exposures in the interbank and asset markets. This alternative approach is able to reduce systemic risk, because it mitigates the adverse effects that the deleveraging of large banks has on the entire banking system. The mitigation effect works via the lower coverage ratio for the less important banks, because they increase liquidity supply in the interbank markets, thereby mitigating liquidity scarcity, and invest in non-liquid assets, thereby compensating the asset liquidation from systemically important banks.

5.4.2 Limiting counterparty risk

An advantage of network models is that they capture interconnections and therefore counterparty risk. From such a network perspective, preventing contagion means limiting counterparty risk. Hałaj and Kok (2015) simulate the effect of two measures intended to limit counterparty risk in an interbank network where banks optimize their balance sheets based on the balance sheet composition of 80 large EU banks. The first policy simulation analyzes credit valuation adjustment, which is the difference between the risk-free portfolio value and the true portfolio value that takes into account the possibility of a counterparty's default. In other words, credit valuation adjustment is the market value of counterparty credit risk. Varying the credit valuation adjustment parameter from no additional capital charges for counterparty risk to a regime with the market-based credit risk valuation of the interbank exposures, Hałaj and Kok (2015) find that the interbank networks structure does not change substantially except for some smaller and weaker banks that are forced to accept less diversified funding sources, because interbank placements are shifted to more sound institutions. The second measure Hałaj and Kok (2015) analyze is large exposure limits.[52] The current EU standard for large exposure limits amounts to 25 percent of total regulatory capital. The degree distribution is relatively stable around and especially above the 25 percent threshold. By contrast, moving the threshold towards 0 percent triggers substantial changes to the structure of the network. This is intuitive, since banks will have to reduce the size of individual exposures and as spread their interbank exposures across more counterparties.

While Hałaj and Kok (2015) analyze relative exposure limits, Gofman (2014) studies absolute exposure limits, namely limits on the number of counterparties. He calibrates a network model of an over-the-counter market based on bilateral trades in the Federal funds market. The calibrated architecture is compared to nine counterfactual architectures with the same number of banks and the same average number of counterparties to each bank, but with different restrictions on the maximum number of counterparties each bank can have.[53] The simulations reveal that the efficiency of liquidity allocation

[52]See also Nier et al. (2007) for a simulation experiment studying the effect of the size of interbank exposures on contagion.

[53]The maximum number of counterparties to a single bank in the nine counterfactual architectures

decreases and the risk of contagion increases non-monotonically as banks face limits on the number of counterparties. Failure of a bank in a regulated (and hence less concentrated) architecture leads to less failures of direct counterparties compared to the number of direct defaults caused by the failure of a very interconnected bank in the calibrated architecture, but the total number of failures is larger in the regulated architecture because the default chains are longer. Overall, the results suggest that it is not optimal to limit the number of a bank's counterparties because it can lead to a banking system that is less efficient and more fragile.

5.4.3 Capital requirements

A capital requirement is the amount of capital a financial institution has to hold as required by the competent regulator. It is defined in terms of a capital ratio, which is the percentage of a bank's capital (also called equity) to its risk-weighted assets. The bank's capital ratio has to be maintained above a certain threshold, as specified by the regulator.

Nier et al. (2007) perform simulation experiments that are designed to study how the resilience of the interbank network is affected by changes in the capital requirement. They find that the better capitalized banks are, the more resilient is the banking system. This effect is non-linear. For very low levels (0 to 1 percent) of net worth to total assets, the number of defaults decreases dramatically. Between 1 and 4 percent of net worth, the number of defaults is constant and between 4 and 5 percent, defaults decrease to zero. But even if banks are well capitalized, levels of interbank activity beyond a certain threshold imply elevated systemic risk.

Bluhm et al. (2014b) simulate the effect of a gradual increase in the capital requirement.[54] Systemic risk exhibits a bell-shaped dynamic. For initially low levels of the capital requirement interbank lending is substantial and driven by banks that have high returns on non-liquid assets. As this phenomenon drives up the interbank interest rate, there are only a few highly profitable banks that borrow large amounts on the interbank market. As Bluhm et al. (2014b) gradually increase the capital requirement, the scope for leveraging is reduced. Consequently, the demand for interbank loans declines, which results in a lower interbank interest rate. The lower interest rate leads to an increase in the number of banks which borrow since their return on non-liquid assets is now higher than the return on the interbank market. As there are more borrowers and less lenders, each bank has fewer counterparties on the interbank market. The system becomes more fragile because the shock to one of the debtor banks is absorbed by a smaller number of creditors. As the capital ratio is increased beyond 7 percent, the activity on the interbank market as well as the investment in non-liquid assets decline. This ultimately results in monotonously decreasing systemic risk, though at the expense of efficiency.

Cifuentes et al. (2005) investigate yet another facet of capital requirements. They study the consequences of mark-to-market accounting of bank's balance sheets in the

ranges from 22 to 120, compared with more than 140 in the calibrated architecture.

[54]Aldasoro et al. (2015) study the effect of an increase in the equity requirement in a similar setup, but featuring risk averse banks.

presence of capital requirements. A drop in the market value of a bank's assets will provoke the sale of assets. If the residual demand curve for these assets is less than perfectly elastic, these asset sales will result in lower market prices. After a price update, satisfying the minimum capital requirement may require further asset sales. These additional sales will again impact market prices. In summary, the interaction of mark-to-market accounting and capital constraints have the potential to endogenously amplify the initial shock.

To conclude this section on policy insights from the financial networks literature, let us briefly dwell on proposals to set systemic regulatory requirements, as for example suggested by Haldane and May (2011). They argue that looking at financial risk through a network lens indicates a fundamentally different rationale for prudential regulation. In their view, prudential regulation has become increasingly risk-based. But the risk to which regulation was then calibrated has tended to be institution-specific rather than systemic risk. Approaching capital requirements from a system-wide angle would require to set firms' capital requirements to equalize the marginal cost to the system as a whole of their failure. In other words, regulatory requirements should be set higher for those banks bringing greatest risk to the system[55]; for example, because of their size or connectivity (Haldane and May, 2011; Arinaminpathy et al., 2012).

6 Conclusion

The literature on interbank networks has grown tremendously in the past years. While this literature has provided us with a number of important insights, a number of important research questions remain. I will use the conclusion to point out a number of open questions that future research might address.

1. More research is needed on the effect of the network structure on contagion. Theoretical interbank network modeling needs to use more realistic network structures on which to analyze contagion processes. Since empirical studies now provide an increasing number of stylized facts on the interbank network topology, research needs to move beyond deriving results on random networks or on overly simplified structures. Theoretical models should indeed be able to replicate topological properties of real-world interbank networks.

2. The focus has been on direct links in the interbank market as well as indirect links in the form of common assets. Yet there are many more types of indirect links in the interbank market. For example credit risk transfers in the form of derivatives[56] are an important source of potential contagion and should therefore be studied more carefully.

[55]In this spirit, Alter et al. (2015) assess capital rules based on network metrics in an interbank network estimated using the detailed German credit register.

[56]For recent work on the CDS market from a network perspective, see Peltonen et al. (2014) and Duffie et al. (2015). More generally, one of the first empirical studies analyzing exposures arising from derivatives contracts between banks is Molina-Borboa et al. (2015).

3. Most interbank network models in the literature are static and exogenously given. One limitation of these static models is that they do not provide a dynamic account of link formation. Research is moving in this direction, but most of the dynamic models still use probabilistic link formation by relying on network growth models or on preferential attachment rules. A few recent models rely on endogenous network formation, in which banks purposefully choose the amount of interbank lending and borrowing and thereby create the structure of the interbank network. More work is needed on how to incorporate bank behavior into interbank networks. More precisely, it is necessary to include micro-founded models of bank's dynamic reactions to financial shocks and to changes in regulatory parameters.

4. A bigger effort should be made to compare results and to exploit complementarities between the financial network literature and the established macro finance literature, since both share similar research topics, such as the study of the propagation and amplification of shocks in the financial system, fire sales spirals, market liquidity or the fragility of financial intermediaries.

5. More research is also needed to evaluate the impact of macro-prudential policy instruments on the financial sector as well as the analysis of the interactions between different macro-prudential policy instruments. Similarly, the evaluation of the interactions between monetary policy and macro-prudential policy is also an interesting topic for further research.

References

Abbassi, P., Bräuning, F., Fecht, F., and Peydro, J. (2014). Cross-border liquidity, relationships and monetary policy: Evidence from the Euro area interbank crisis. *Bundesbank Discussion Paper No 45.*

Acemoglu, D., Ozdaglar, A., and Tahbaz-Salehi, A. (2015a). Systemic risk and stability in financial networks. *American Economic Review*, 105(2):564–608.

Acemoglu, D., Ozdaglar, A., and Tahbaz-Salehi, A. (2015b). Systemic risk in endogenous financial networks. *Columbia Business School Research Paper*, No. 15-17.

Affinito, M. (2012). Do interbank customer relationships exist? And how did they function in the crisis? Learning from Italy. *Journal of Banking & Finance*, 36(12):3163–3184.

Albert, R., Jeong, H., and Barabási, A.-L. (2000). Error and attack tolerance of complex networks. *Nature*, 406(6794):378–382.

Aldasoro, I. and Alves, I. (2015). Multiplex interbank networks and systemic importance: An application to European data. *SAFE Working Paper*, No. 102.

Aldasoro, I. and Angeloni, I. (2015). Input-output-based measures of systemic importance. *Quantitative Finance*, 15(4).

Aldasoro, I., Delli Gatti, D., and Faia, E. (2015). Bank networks: Contagion, systemic risk and prudential policy. *CEPR Discussion Paper No. 10540.*

Aldasoro, I. and Faia, E. (2015). Liquidity and contagion. Unpublished manuscript.

Allen, F. and Babus, A. (2009). Networks in finance. In Kleindorfer, P. R. and Wind, Y., editors, *The network challenge: strategy, profit, and risk in an interlinked world*, pages 367–382. Prentice Hall Professional.

Allen, F., Babus, A., and Carletti, E. (2012). Asset commonality, debt maturity and systemic risk. *Journal of Financial Economics*, 104(3):519–534.

Allen, F., Carletti, E., Krahnen, J.-P., and Mark, T. (2011). *Liquidity and crises.* Oxford University Press.

Allen, F. and Gale, D. (2000). Financial contagion. *Journal of Political Economy*, 108(1):1–33.

Alter, A., Craig, B., and Raupach, P. (2015). Centrality-based capital allocations. *International Journal of Central Banking.*

Alves, I., Ferrari, S., Franchini, P., Heam, J., Jurca, P., Langfield, S., Laviola, S., Liedorp, F., Sánchez, A., Tavolaro, S., and Vuillemey, G. (2013). The structure and resilience of the European interbank market. *ESRB Occasional Papers*, 3.

Amini, H., Cont, R., and Minca, A. (2013). Resilience to contagion in financial networks. *Mathematical Finance.* DOI: 10.1111/mafi.12051.

Anand, K., Bédard-Pagé, G., and Traclet, V. (2014). Stress testing the Canadian banking system: A system-wide approach. *Bank of Canada Financial Stability Review.*

Anand, K., Craig, B., and von Peter, G. (2015). Filling in the blanks: Network structure and interbank contagion. *Quantitative Finance*, 15(4).

Anand, K., Gai, P., Kapadia, S., Brennan, S., and Willison, M. (2013). A network model of financial system resilience. *Journal of Economic Behavior & Organization*, 85:219 – 235.

Anand, K., Gai, P., and Marsili, M. (2012). Rollover risk, network structure and systemic financial crises. *Journal of Economic Dynamics and Control*, 36(8):1088–1100.

Arinaminpathy, N., Kapadia, S., and May, R. M. (2012). Size and complexity in model financial systems. *Proceedings of the National Academy of Sciences*, 109(45):18338–18343.

Arregui, M. N., Norat, M. M., Pancorbo, A., Scarlata, J. G., Holttinen, E., Melo, F., Surti, J., Wilson, C., Wehrhahn, R., and Yanase, M. (2013). Addressing interconnectedness: Concepts and prudential tools. *IMF Working Paper Series*, 13(199).

Barabási, A.-L. and Albert, R. (1999). Emergence of scaling in random networks. *Science*, 286(5439):509–512.

Bargigli, L., di Iasio, G., Infante, L., Lillo, F., and Pierobon, F. (2014). The multiplex structure of interbank networks. *Quantitative Finance*, 15(4).

Basel Committee on Banking Supervision (2013). Global systemically important banks: Updated assessment methodology and the higher loss absorbency requirement. Framework text, Bank of International Settlements.

Battiston, S., Gatti, D. D., Gallegati, M., Greenwald, B., and Stiglitz, J. E. (2012a). Default cascades: When does risk diversification increase stability? *Journal of Financial Stability*, 8(3):138 – 149.

Battiston, S., Gatti, D. D., Gallegati, M., Greenwald, B., and Stiglitz, J. E. (2012b). Liaisons dangereuses: Increasing connectivity, risk sharing, and systemic risk. *Journal of Economic Dynamics and Control*, 36(8):1121 – 1141.

Battiston, S., Puliga, M., Kaushik, R., Tasca, P., and Caldarelli, G. (2012c). Debtrank: Too central to fail? Financial networks, the Fed and systemic risk. *Scientific reports*, 2(541).

Bech, M. L. and Atalay, E. (2010). The topology of the federal funds market. *Physica A: Statistical Mechanics and its Applications*, 389(22):5223–5246.

Benoit, S., Colliard, J.-E., Hurlin, C., and Pérignon, C. (2015). Where the risks lie: A survey on systemic risk. *HEC Paris Research Paper*, No. FIN-2015-1088.

Bhattacharya, S. and Gale, D. (1987). Preference shocks, liquidity and central bank policy. In Barnett, W. and Singleton, K., editors, *New Approaches to Monetary Economics*, pages 69–88. Cambridge University Press.

Billio, M., Getmansky, M., Lo, A. W., and Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, 104(3):535 – 559.

Bisias, D., Flood, M., Lo, A. W., and Valavanis, S. (2012). A survey of systemic risk analytics. *Annual Review of Financial Economics*, 4(1):255–296.

Bluhm, M., Faia, E., and Krahnen, J. P. (2014a). Endogenous banks' networks, cascades and systemic risk. *SAFE Working Paper Series*, 12.

Bluhm, M., Faia, E., and Krahnen, J. P. (2014b). Monetary policy implementation in an interbank network: Effects on systemic risk. *SAFE Working Paper Series*, 46.

Blume, L., Easley, D., Kleinberg, J., Kleinberg, R., and Tardos, É. (2011). Which networks are least susceptible to cascading failures? In *Foundations of Computer Science (FOCS), 2011 IEEE 52nd Annual Symposium on*, pages 393–402.

Blume, L., Easley, D., Kleinberg, J., Kleinberg, R., and Tardos, E. (2013). Network formation in the presence of contagious risk. *ACM Transactions on Economics and Computation*, 1(2):6.

Borgatti, S. P. (2005). Centrality and network flow. *Social networks*, 27(1):55–71.

Boss, M., Elsinger, H., Summer, M., and Thurner, S. (2004). Network topology of the interbank market. *Quantitative Finance*, 4(6):677–684.

Bräuning, F., Blasques, F., and van Lelyveld, I. (2015). A dynamic network model of the unsecured interbank lending market. *BIS Working Papers No 491.*

Bräuning, F. and Fecht, F. (2012). Relationship lending in the interbank market and the price of liquidity. *Deutsche Bundesbank Discussion Paper*, 2012(22).

Brunnermeier, M. K., Eisenbach, T., and Sannikov, Y. (2013). Macroeconomics with financial frictions: A survey. In Acemoglu, D., Arellano, M., and Dekel, E., editors, *Advances in Economics and Econometrics, Tenth World Congress of the Econometric Society*. Cambridge University Press, New York.

Brunnermeier, M. K. and Pedersen, L. H. (2009). Market liquidity and funding liquidity. *Review of Financial Studies*, 22(6):2201–2238.

Brusco, S. and Castiglionesi, F. (2007). Liquidity coinsurance, moral hazard, and financial contagion. *The Journal of Finance*, 62(5):2275–2302.

Caballero, R. J. and Simsek, A. (2013). Fire sales in a model of complexity. *The Journal of Finance*, 68(6):2549–2587.

Caccioli, F., Farmer, J. D., Foti, N., and Rockmore, D. (2015). Overlapping portfolios, contagion, and financial stability. *Journal of Economic Dynamics and Control*, 51:5063.

Caccioli, F., Shrestha, M., Moore, C., and Farmer, J. D. (2014). Stability analysis of financial contagion due to overlapping portfolios. *Journal of Banking & Finance*, 46:233 – 245.

Canedo, J. M. D. and Jaramillo, S. M. (2009). A network model of systemic risk: Stress testing the banking system. *Intelligent Systems in Accounting, Finance & Management*, 16(1-2):87–110.

Chan-Lau, J., Espinosa, M., Giesecke, K., and Solé, J. (2009). Assessing the systemic implications of financial linkages. *IMF Global Financial Stability Report*, Chapter 2:73–110.

Chinazzi, M. and Fagiolo, G. (2013). Systemic risk, contagion, and financial networks: A survey. *LEM Working Paper Series*, No. 8.

Cifuentes, R., Ferrucci, G., and Shin, H. S. (2005). Liquidity risk and contagion. *Journal of the European Economic Association*, 3(2-3):556–566.

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

Cohen-Cole, E., Patacchini, E., and Zenou, Y. (2015). Static and dynamic networks in interbank markets. *Network Science*. DOI: 10.1017/nws.2015.1.

Cont, R., Moussa, A., and Santos, E. B. (2013). Network structure and systemic risk in banking systems. In Fouque, J.-P. and Langsam, J. A., editors, *Handbook on Systemic Risk*, pages 327–368. Cambridge University Press. Cambridge Books Online.

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

Dasgupta, A. (2004). Financial contagion through capital connections: A model of the origin and spread of bank panics. *Journal of the European Economic Association*, 2(6):1049–1084.

De Bandt, O., Hartmann, P., and Peydro, J. (2012). Systemic risk in banking: An update. In Berger, A., Molyneux, P., and Wilson, J., editors, *The Oxford Handbook of Banking*, pages 633–672. Oxford University Press.

De Masi, G., Iori, G., and Caldarelli, G. (2006). Fitness model for the Italian interbank money market. *Phys. Rev. E*, 74:066112.

Della Rossa, F., Dercole, F., and Piccardi, C. (2013). Profiling core-periphery network structure by random walkers. *Scientific reports*, 3.

Diamond, D. W. and Dybvig, P. H. (1983). Bank runs, deposit insurance, and liquidity. *The Journal of Political Economy*, 91(3):401–419.

Duffie, D., Scheicher, M., and Vuillemey, G. (2015). Central clearing and collateral demand. *Journal of Financial Economics*, 116(2):237–256.

ECB (2006). Identifying large and complex banking groups for financial system stability analysis. *ECB Financial Stability Review*, pages 131–139.

Eisert, T. and Eufinger, C. (2014). Interbank network and bank bailouts: Insurance mechanism for non-insured creditors? *SAFE Working Paper*, No. 10.

Elliott, M., Golub, B., and Jackson, M. O. (2014). Financial networks and contagion. *American Economic Review*, 104(10):31153153.

Elsinger, H., Lehar, A., and Summer, M. (2006). Risk assessment for banking systems. *Management Science*, 52(9):1301–1314.

Elsinger, H., Lehar, A., and Summer, M. (2013). Network models and systemic risk assessment. In Fouque, J.-P. and Langsam, J. A., editors, *Handbook on Systemic Risk*, pages 287–305. Cambridge University Press.

Espinosa-Vega, M. and Solé, J. (2014). Introduction to the network analysis approach to stress testing. In Ong, L., editor, *A Guide to IMF Stress Testing: Methods and Models*, chapter 13, pages 205–208. International Monetary Fund.

Farboodi, M. (2014). Intermediation and voluntary exposure to counterparty risk. Unpublished manuscript.

Fique, J. and Page, F. (2013). Rollover risk and endogenous network dynamics. *Computational Management Science*, 10(2-3):213–230.

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

Freixas, X., Parigi, B. M., and Rochet, J.-C. (2000). Systemic risk, interbank relations, and liquidity provision by the central bank. *Journal of Money, Credit and Banking*, 32(3):611–638.

Fricke, D. and Lux, T. (2015a). Core-periphery structure in the overnight money market: Evidence from the e-MID trading platform. *Computational Economics*, 45:359–395.

Fricke, D. and Lux, T. (2015b). On the distribution of links in the interbank network: Evidence from the e-MID overnight money market. *Empirical Economics*. DOI: 10.1007/s00181-015-0919-x.

Furfine, C. H. (1999). The microstructure of the federal funds market. *Financial Markets, Institutions & Instruments*, 8(5):24–44.

Furfine, C. H. (2003). Interbank exposures: Quantifying the risk of contagion. *Journal of Money, Credit and Banking*, 35(1):111–28.

Gai, P., Haldane, A., and Kapadia, S. (2011). Complexity, concentration and contagion. *Journal of Monetary Economics*, 58(5):453–470.

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

Garratt, R. J., Mahadeva, L., and Svirydzenka, K. (2014). The great entanglement: The contagious capacity of the international banking network just before the 2008 crisis. *Journal of Banking & Finance*, 49:367–385.

Geanakoplos, J. (2010). The leverage cycle. In *NBER Macroeconomics Annual 2009, Volume 24*, pages 1–65. University of Chicago Press.

Georg, C.-P. (2013). The effect of the interbank network structure on contagion and common shocks. *Journal of Banking & Finance*, 37(7):2216–2228.

Georgescu, O.-M. (2015). Contagion in the interbank market: Funding versus regulatory constraints. *Journal of Financial Stability*, 18:1 – 18.

Glasserman, P. and Young, H. P. (2015). How likely is contagion in financial networks? *Journal of Banking & Finance*, 50:383399.

Gofman, M. (2014). Efficiency and stability of a financial architecture with too-interconnected-to-fail institutions. Unpublished manuscript.

Greenwood, R., Landier, A., and Thesmar, D. (2015). Vulnerable banks. *Journal of Financial Economics*, 115(3):471 – 485.

Halaj, G., Kochanska, U., and Kok, C. (2015). Emergence of the EU corporate lending network. *Journal of Network Theory in Finance*, 1(1).

Hałaj, G. and Kok, C. (2015). Modeling emergence of the interbank networks. *Quantitative Finance*, 15(4).

Haldane, A. G. (2009). Rethinking the financial network. Speech delivered at the Financial Student Association, Amsterdam, April 2009.

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

Ho, T. S. and Saunders, A. (1985). A micro model of the federal funds market. *The Journal of Finance*, 40(3):977–988.

In't Veld, D., van der Leij, M., and Hommes, C. (2014). The formation of a core periphery structure in heterogeneous financial networks. *Tinbergen Institute Discussion Paper*, 14-098.

Iori, G., Mantegna, R. N., Marotta, L., Miccich, S., Porter, J., and Tumminello, M. (2015). Networked relationships in the e-MID interbank market: A trading model with memory. *Journal of Economic Dynamics and Control*, 50(0):98 – 116.

Iori, G., Masi, G. D., Precup, O. V., Gabbi, G., and Caldarelli, G. (2008). A network analysis of the Italian overnight money market. *Journal of Economic Dynamics and Control*, 32(1):259 – 278.

Jackson, M. O. (2005). A survey of network formation models: Stability and efficiency. In Demange, G. and Wooders, M., editors, *Group Formation in Economics*, pages 11–57. Cambridge University Press. Cambridge Books Online.

Jackson, M. O. (2010). *Social and economic networks*. Princeton University Press.

Jackson, M. O. and Wolinsky, A. (1996). A strategic model of social and economic networks. *Journal of Economic Theory*, 71(1):44–74.

Laeven, L. and Valencia, F. (2013). Systemic banking crises database. *IMF Economic Review*, 61(2):225–270.

Lagunoff, R. and Schreft, S. L. (2001). A model of financial fragility. *Journal of Economic Theory*, 99(1):220–264.

Langfield, S., Liu, Z., and Ota, T. (2014). Mapping the UK interbank system. *Journal of Banking & Finance*, 45:288 – 303.

Langfield, S. and Soramäki, K. (2014). Interbank exposure networks. *Computational Economics*. DOI: 10.1007/s10614-014-9443-x.

Leitner, Y. (2005). Financial networks: Contagion, commitment, and private sector bailouts. *The Journal of Finance*, 60(6):2925–2953.

Lenzu, S. and Tedeschi, G. (2012). Systemic risk on different interbank network topologies. *Physica A: Statistical Mechanics and its Applications*, 391(18):4331 – 4341.

Léon, C. and Berndsen, R. J. (2014). Rethinking financial stability: Challenges arising from financial networks' modular scale-free architecture. *Journal of Financial Stability*, 15(0):241 – 256.

Lux, T. (2014). Emergence of a core-periphery structure in a simple dynamic model of the interbank market. *Journal of Economic Dynamics and Control*, 52:A11–A23.

May, R. M. and Arinaminpathy, N. (2009). Systemic risk: The dynamics of model banking systems. *Journal of The Royal Society Interface*, 7(46):823–838.

Minoiu, C. and Reyes, J. A. (2013). A network analysis of global banking: 1978–2010. *Journal of Financial Stability*, 9(2):168–184.

Mistrulli, P. E. (2011). Assessing financial contagion in the interbank market: Maximum entropy versus observed interbank lending patterns. *Journal of Banking & Finance*, 35(5):1114 – 1127.

Molina-Borboa, J., Martinez-Jaramillo, S., Lopez-Gallo, F., and van der Leij, M. (2015). A multiplex network analysis of the mexican banking system: link persistence, overlap and waiting times. *Journal of Network Theory in Finance*, 1(1):99–138.

Montagna, M. and Kok, C. (2013). Multi-layered interbank model for assessing systemic risk. *Kiel Working Paper*, 1873.

Montagna, M. and Lux, T. (2013). Hubs and resilience: Towards more realistic models of the interbank markets. *Kiel Working Paper No. 1826.*

Nier, E., Yang, J., Yorulmazer, T., and Alentorn, A. (2007). Network models and financial stability. *Journal of Economic Dynamics and Control*, 31(6):2033–2060.

Peltonen, T. A., Scheicher, M., and Vuillemey, G. (2014). The network structure of the CDS market and its determinants. *Journal of Financial Stability*, 13:118 – 133.

Sheldon, G. and Maurer, M. (1998). Interbank lending and systemic risk: An empirical analysis for Switzerland. *Swiss Journal of Economics and Statistics*, 134(IV).

Shin, H. S. (2010). *Risk and liquidity*. Oxford University Press.

Soramäki, K., Bech, M. L., Arnold, J., Glass, R. J., and Beyeler, W. E. (2007). The topology of interbank payment flows. *Physica A: Statistical Mechanics and its Applications*, 379(1):317 – 333.

Soramäki, K. and Cook, S. (2013). Sinkrank: An algorithm for identifying systemically important banks in payment systems. *Economics: The Open-Access, Open-Assessment E-Journal*, 7(2013-28):1–27.

Summer, M. (2013). Financial contagion and network analysis. *Annual Review of Financial Economics*, 5(1):277–297.

Tonzer, L. (2015). Cross-border interbank networks, banking risk and contagion. *Journal of Financial Stability*, 18:19–32.

Upper, C. (2011). Simulation methods to assess the danger of contagion in interbank markets. *Journal of Financial Stability*, 7(3):111 – 125.

Upper, C. and Worms, A. (2004). Estimating bilateral exposures in the german interbank market: Is there a danger of contagion? *European Economic Review*, 48(4):827 – 849.

Veld, D. I. and van Lelyveld, I. (2014). Finding the core: Network structure in interbank markets. *Journal of Banking & Finance*, 49:27 – 40.

Vivier-Lirimont, S. (2006). Contagion in interbank debt networks. Unpublished Manuscript.

Watts, D. J. and Strogatz, S. H. (1998). Collective dynamics of small-world networks. *Nature*, 393(6684):440–442.

Wells, S. (2004). Financial interlinkages in the United Kingdom's interbank market and the risk of contagion. *Bank of England Quarterly Bulletin*, 44(3):331.

Recent Issues

No. 90	Pinar Topal	**Fiscal Stimulus and Labor Market Flexibility**
No. 89	Julia Braun, Alfons J. Weichenrieder	**Does Exchange of Information between Tax Authorities Influence Multinationals' Use of Tax Havens?**
No. 88	Ester Faia, Beatrice Weder di Mauro	**Cross-Border Resolution of Global Banks**
No. 87	Iñaki Aldasoro, Domenico Delli Gatti, Ester Faia	**Bank Networks: Contagion, Systemic Risk and Prudential Policy**
No. 86	Agar Brugiavini, Danilo Cavapozzi, Mario Padula, Yuri Pettinicchi	**Financial education, literacy and investment attitudes**
No. 85	Holger Kraft, Claus Munk, Sebastian Wagner	**Housing Habits and Their Implications for Life-Cycle Consumption and Investment**
No. 84	Raimond Maurer, Olivia S. Mitchell, Ralph Rogalla, Tatjana Schimetschek	**Will They Take the Money and Work? An Empirical Analysis of People's Willingness to Delay Claiming Social Security Benefits for a Lump Sum**
No. 83	Patrick Grüning	**International Endogenous Growth, Macro Anomalies, and Asset Prices**
No. 82	Edgar Vogel, Alexander Ludwig, Axel Börsch-Supan	**Aging and Pension Reform: Extending the Retirement Age and Human Capital Formation**
No. 81	Jens-Hinrich Binder	**Resolution Planning and Structural Bank Reform within the Banking Union**
No. 80	Enrique G. Mendoza, Linda L. Tesar, Jing Zhang	**Saving Europe?: The Unpleasant Arithmetic of Fiscal Austerity in Integrated Economies**
No. 79	Òscar Jordà, Alan M. Taylor	**The Time for Austerity: Estimating the Average Treatment Effect of Fiscal Policy**
No. 78	Harris Dellas, Dirk Niepelt	**Austerity**
No. 77	Benjamin Born, Gernot J. Müller, Johannes Pfeifer	**Does Austerity Pay Off?**
No. 76	Alberto Alesina, Carlo Favero, Francesco Giavazzi	**The Output Effect of Fiscal Consolidation Plans**