

Lux, Thomas

Working Paper

Network effects and systemic risk in the banking sector

FinMaP-Working Paper, No. 62

Provided in Cooperation with:

Collaborative EU Project FinMaP - Financial Distortions and Macroeconomic Performance, Kiel University et al.

Suggested Citation: Lux, Thomas (2016) : Network effects and systemic risk in the banking sector, FinMaP-Working Paper, No. 62, Kiel University, FinMaP - Financial Distortions and Macroeconomic Performance, Kiel

This Version is available at:

<https://hdl.handle.net/10419/130157>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

FinMaP-Working Paper No.62



This project has received funding from the European Union's Seventh Framework Programme for research, technological development and demonstration under grant agreement no. 612955



FINMAP –

**FINANCIAL DISTORTIONS AND MACROECONOMIC
PERFORMANCE: EXPECTATIONS, CONSTRAINTS AND
INTERACTION OF AGENTS**

DATE: 03/22/2016

TITLE

Network Effects and Systemic Risk in the Banking Sector

by: Thomas Lux

ABSTRACT

This paper provides a review of recent research on the structure of interbank relations and theoretical models developed to assess the contagious potential of shocks (default of single units) via the interbank network. The empirical literature has established a set of stylized facts that includes a fat-tailed distribution of the number of banks, disassortativity of credit links and a pronounced persistence of existing links over time. These topological features correspond to the existence of money center banks, the importance of relationship banking and the self-organization of the interbank market into a core-periphery structure. Models designed to replicate these topological features exhibit on average more contagious potential than baseline models for the generation of random networks (such as the Erdős-Renyi or preferential attachment mechanisms) that do not share the stylized facts. Combining different channels of contagion such as interbank exposures, portfolio overlaps and common exposure to non-financial borrowers, one typically finds that different contagion channels interact in a distinctly nonlinear way.

Dedicated to Gerhard Illing on the occasion of his 60th birthday.

AUTHORS

1. **Thomas Lux**

Department of Economics,
Kiel University
D24098 Kiel

Department of Economics
Chair in Computational Economics
University Jaume I
Es- Castellon

Email: lux@economics.uni-kiel.de

Network Effects and Systemic Risk in the Banking Sector*

Thomas Lux[†]

Abstract

This paper provides a review of recent research on the structure of interbank relations and theoretical models developed to assess the contagious potential of shocks (default of single units) via the interbank network. The empirical literature has established a set of stylized facts that includes a fat-tailed distribution of the number of banks, disassortativity of credit links and a pronounced persistence of existing links over time. These topological features correspond to the existence of money center banks, the importance of relationship banking and the self-organization of the interbank market into a core-periphery structure. Models designed to replicate these topological features exhibit on average more contagious potential than baseline models for the generation of random networks (such as the Erdős-Renyi or preferential attachment mechanisms) that do not share the stylized facts. Combining different channels of contagion such as interbank exposures, portfolio overlaps and common exposure to non-financial borrowers, one typically finds that different contagion channels interact in a distinctly nonlinear way.

Dedicated to Gerhard Illing on the occasion of his 60th birthday.

1 Introduction

The field of economics had been caught completely unprepared for the worldwide financial crisis that broke out in 2007/2008 and to some extent still continues to date. It then seemed to many observers that the economics profession had obviously ignored many important factors and relationships in financial markets. Indeed, as it concerns

*I am very grateful to Zhenxi Chen, Lutz Honvehlmann, Mattia Montagna and Matthias Raddant for discussions and research assistance in the preparation of this manuscript. The most helpful comments by Frank Heinemann are also gratefully acknowledged. The research reported in this paper has received funding from the Spanish Ministry of Science and Innovation (ECO2011-23634), from Universitat Jaume I (P1.1B2012-27) and from the European Union Seventh Framework Programme (FP7/2007-2013) under grant agreement no. 612955.

[†]Department of Economics, University of Kiel and Banco de España Chair in Computational Economics, University Jaume I

macroeconomic research the pre-2008 mainstream approach had deliberately blinded out the financial system in its entirety in its prevalent models because of the purported “efficiency” of financial markets (cf. Lux, 2013). The inability of economic models to recognize developments that could exacerbate crises and to explore real-world developments rather than by exogenous ‘shocks’ has led to a heated and still ongoing debate on methodological deficits of this field. Paul Krugman, a 2008 Nobel laureate, has stated that the last 30 years of macroeconomic and financial market research have been in his view “spectacularly useless at best and positively harmful at worst” (cf. *The Economist*, July 18th, 2009). Others have emphasized that economists are themselves responsible for the negligence of financial distortions by policy makers and regulators, since their then dominating paradigm painted an illusory picture of a financial sector that is governed only by rational behavior and in which phenomena like speculative bubbles, crashes and manias (to quote the title of a famous book on the history of financial crisis, Kindleberger and Aliber, 2005) are not known of.

Particularly after the default of Lehman Brothers, one of the major U.S. investment banks, in September 2008, the crisis appeared to spread like a disease. It emanated from the U.S. real estate market and complex new derivatives, so-called Collateralized Debt Obligations (CDO) that made default risk marketable. This caused overinvestment in the housing market by extension of credit to ‘sub-prime’ borrowers. When it became obvious, that house prices would decline and many of the bad risks would materialize themselves (and many mortgage loans and the CDOs based on these became ‘toxic’) the crisis very quickly spread beyond its local origin and in a matter of days reached far-flung financial institutions and brought many banks and even complete financial systems (such as Iceland’s) to the verge of default and collapse.

The diagnosis of unfolding events brought topics to the fore which have been hardly considered of interest in financial economics before. A new research agenda had been launched to assess the potential of systemic risks in the banking sector and help policy makers to develop an efficient regulatory design (cf. Illing, 2012). One of the important ingredients of this research is the investigation of the *network structure* of connections within the banking sector. Only by ‘mapping’ and understanding this network structure it will be possible to understand the contagious spread of stress and to design regulations to prevent system-wide (systemic) crises to materialize under adverse conditions. The robustness and fragility of different network structures is a topic that has been dealt with extensively in the natural sciences. Economics, which has been strongly oriented at a micro-perspective (focusing on the analysis of single actors) has been lacking such a perspective on the interplay of actors and its resulting macroscopic consequences. A few attempts to look at the role of connections did, however, exist: Allen and Gale (2000) studied interbank lending in a simple financial system composed of four banks, and with their framework provided a blueprint for subsequent extensions and generalizations that

started to mushroom after the relevance of this channel of stress propagation became apparent (e.g. Nier et al., 2008; Haldane and May, 2011). From the side of practitioners, many central banks have conducted tests of the contagious potential in the interbank market using data sets for the interbank liabilities of their national financial system (cf. Upper and Worms, 2004). Sometimes, physicists have been provided access to such data to study its network properties (cf. Boss et al., 2004, Soramäki et al., 2007).

The aim of this paper is to provide a review of recent research in this area by the author and his research groups at the University of Kiel and the University Jaume I. The basic objective of this research has been:

- To add to our empirical knowledge of the structure and topology of the network of financial connections between financial institutions and, if possible, to extract its prevalent characteristics or (as economists call it) its ‘stylized facts’.¹
- To expand existing models to add more relevant channels of cross-influence beyond interbank credit. For instance, banks are also connected (in sometimes complicated ways) via their derivative positions, by overlap of portfolio composition, by joint exposure to the same creditors or borrowers etc. The aim, then, would be to study potential contagion effects via multiple channels in what is called a multiplex (multi-dimensional) network structure.
- To add behavioral aspects and dynamics to the so far static and mechanical structure of interbank network models. Such models would make it possible to study endogenous adjustments of market participants that go beyond a mechanical transmission of shocks via losses, and would hopefully allow understanding the dynamic process behind the formation of the very particular network structure in the financial sector.

The next sections provide an overview of the research conducted on these different research questions.

2 The Structure and Development of Credit Relationships in the Banking Sector

2.1 Extracting the “Stylized Facts”

Analysis of the network structure of the financial sector is very much hampered by the lack of openly accessible data sources. In contrast to many other areas of economic activity, few data exist that are available to interested researchers. And also very much in contrast

¹Those features that remain constant over time and across ‘space’, i.e. for data from different countries.

to the ubiquity of information on many other aspects of human activity, the financial sector is still the most opaque part of the economic sphere. Data sets that have been collected and investigated at various central banks are typically subject to confidentiality and they cover only snapshots of selected financial linkages over certain time windows for certain instruments and maturities and with a limited coverage of the pertinent banking sector (e.g. only covering the largest banks or exposures beyond a certain threshold). The only commercially available data set for interbank credit is the recorded trading activity in the trading platform e-MID (electronic market for interbank deposits). This is a screen-based system for the exchange of unsecured money market deposits in various currencies operated in Milan by e-MID SpA. This system offers centralized access to bids and asks for interbank credit by a large number of participating banks. In 2006, for instance, it accounted for approximately 17% of total turnover in the unsecured money market of the EURO area with a volume of 24.2 bn. Euros. In the absence of other data sets, the recorded trading activity of this market provides at least some partial insights into the structure of interbank credit formation, and the resulting network topology.

Fig. 1 shows a network image of the trading activity aggregated over one quarter. Time aggregation indeed turned out to be essential, at least for interbank credit in the overnight money market. Using daily or weekly data would provide snapshots that are too short to cover prevalent longer lasting credit relationships (credit lines) since most of them will not be activated over a short time horizon, but actually could have been relied upon when the need would have arisen. As it turned out, many network statistics show high variability over short horizons, but exhibited remarkable stability at the monthly to quarterly aggregation level (Fricke et al., 2013). Hence, in order to reduce the influence of noise and to capture most of the hidden structure of available credit lines, analysis of these data at lower frequencies appears preferable. The most salient features of the e-MID data appeared to be the following:

- Sparseness of the network: only a small fraction of all possible links do actually exist in interbank credit networks,
- A high persistency of links: In network theory, this is measured by the so-called Jaccard index (the number of links existing jointly in two adjacent time intervals). In the electronic platform, about 50-60 percent of links survive from one month or quarter to the next² which given the sparseness of links points strongly towards a non-random process of deliberate formation of persistent links,
- Disassortativity of link formation: typically two banks with a credit relationship assume very different positions within the overall network. In particular, the two

²This high persistence would be almost completely concealed when only considering high-frequency data as it had sometimes been done in the early literature. The reason is that existing credit lines would simply not be activated on each and every day.

nodes are negatively correlated in terms of their *degree*, their overall number of links. This means that (as a tendency across the whole system) credit is exchanged mostly between well-connected banks and those that have relatively few connections.

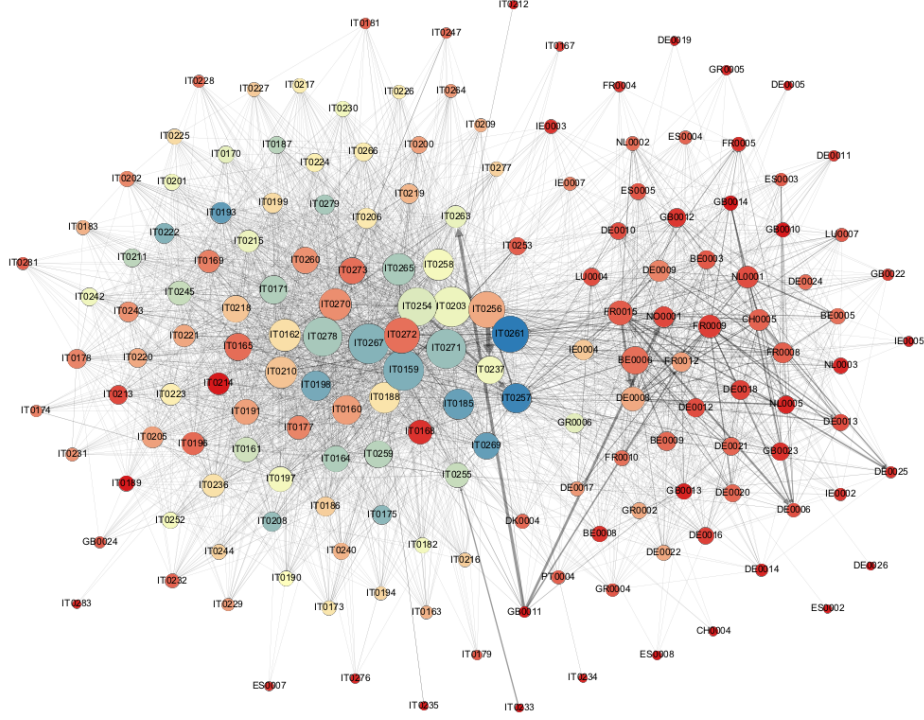


Figure 1: Network image of the interbank credit transactions processed via the electronic trading system e-MID during the second quarter of 2007. Since e-MID is physically located in Italy, it is mostly used by Italian banks. The graphical representation, therefore, distinguishes between Italian banks and foreign banks as indicated by the country coding in the first two digits of their code numbers (e.g., IT, DE etc). The directed links capture the flow of credit from lenders to borrowers. Colors are used to enhance visibility.

A high Jaccard index is in line with the view that the interbank credit market is not an ideal anonymous, atomistic market but that the evaluation of strong preferential relationships is decisive for this market's particular structure (cf. Raddant, 2014). This finding is actually the imprint of the well-known feature of “relationship banking” from a network perspective. Cocco et al. (2009) provide independent evidence for strong persistence of credit links in the interbank market. Disassortativity provides support to the view that some banks assume the role of money center banks that provide credit and absorb liquidity from many other, mostly smaller banks. The network approach, thus,

identifies “stylized facts” in line with existing theories (e.g. relationship banking), but provides a new avenue towards quantitatively covering such presumed features.

2.2 Fitting Structural Models: Scale-Free and Core-Periphery Models for the Banking Network

Over the last decades, network theory as developed in the natural sciences, has brought forward a range of prototypical network structures, such as Erdős-Rényi networks with completely random assignments of links, scale-free networks and small-world networks, for instance. Scale-free networks and small-world networks are characterized by a much broader distribution of links than the Poisson distribution characterizing random networks. Their degree distribution (degrees being the directed or undirected number of credit relationships within a period) follows a power-law which means that some nodes of the network have many more links than the average. One of the popular ways to model such structures is via “preferential attachment”, i.e. newly established nodes prefer to attach themselves to those nodes that already have many links. Small-world networks are structures in which the link topology allows one to move from any node to any other by “navigating” through a small number of links. Indeed, financial networks do have mostly such a small-world topology which means that shocks (defaults) can easily spread all over the system.

The early literature has typically claimed some proximity of financial networks to the scale-free model, reporting an “interesting” (i.e. not too high) estimate of the presumed power-law coefficient, e.g. Boss et al. (2004), de Masi et al. (2006), Soramäki et al. (2007). Reinvestigating such claims for the e-MID data, we did not find any support at all for such a power-law. Simple visual inspection already speaks against it (cf. Fig. 2) and a more rigorous statistical analysis demonstrates that many alternative distributions provide a better fit than a power-law. It seems that in the interbank network literature an unfortunate tradition has been established that researchers “have to” report some power-law statistics which, in the absence of goodness-of-fit tests, is essentially meaningless and uninformative (this practice has also been criticized in other areas of network research, cf. Stumpf and Porter, 2012). Finger et al. (2013) also show that the data under investigation deviate in other respects from those of prototypical scale-free networks. While “preferential attachment” might have been an attractive mechanism for generating money center banks in a financial network, these results show that this generating principle cannot be adopted one-to-one for credit links between banks.

Instead of physics-inspired models, a model initially developed in sociology turned out to provide a better description of such data. Borgatti and Everett (1999) had first proposed to study core-periphery (CP) topologies of network formation (applying those, for example, to data of friendship networks). The organizing principle of a CP network

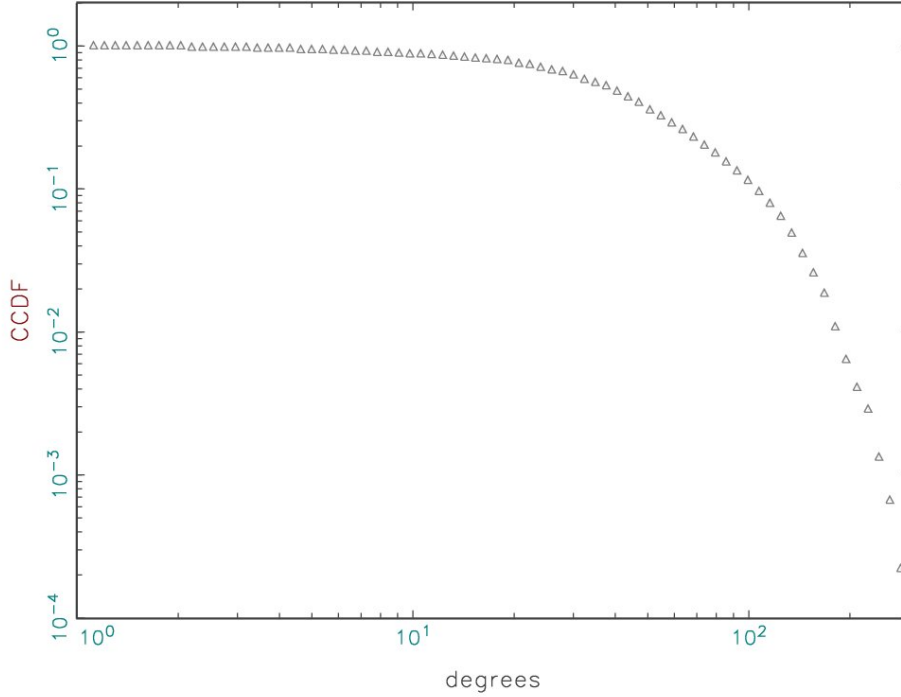


Figure 2: Complementary cumulative distribution functions for the degrees (number of network links) of banks participating in the e-MID electronic market at quarterly aggregation level. Data are pooled over the entire available time horizon 1999 to 2014. A power-law distribution would require an approximately linear slope of the distribution functions in the present log-log scale. The pronounced curvature in the distributions, however, indicates that the power-law hypothesis should be rejected for these data which is also confirmed by more rigorous statistical tests (in Fricke and Lux, 2015b).

model is the classification of links into those forming the core and those being more peripheral to the network. A *discrete* CP model classifies the nodes into this dichotomic scheme by assuming that (i) core nodes are all connected to each other, (ii) peripheral nodes are not connected within their group at all but (iii) have only a limited number of connections to nodes in the core. In its simplest form the discrete CP model provides a data-driven algorithm to identify the *number and identity* of the core members of a community characterized by a network. In so doing, one optimizes an objective function based upon the above characteristics of a CP network (minimizing the discrepancy between the empirical network structure and an idealized pattern that corresponds to a structure that entirely satisfies the assumptions of a CP network). This model turned out to provide a very robust characterization to the e-MID data insofar as the assignment of banks to core and periphery showed very little variation over time, and the activity within the core, within the periphery and between core and periphery were all distinctly different (and consistently so over time) i.e. the very identifying assumptions of a CP structure could all be verified. Fig. 3 provides a typical visualization of the data-driven dichotomization into

core and periphery in one quarter. In a continuous asymmetric extension of the baseline CP framework we showed that the coreness (degree of core membership) of a bank in terms of its ingoing and outgoing links (borrowing and lending in the interbank market), were completely uncorrelated. Hence, a certain bank might, for instance, be one of the core banks in terms of its role as a lender, but might be less important as a borrower: some mainly provide liquidity to the system; others absorb liquidity (Fricke and Lux, 2015a).³

The CP framework also allowed shedding some light on the intricate changes of behavior in the beginning of the financial crisis in 2008. Disentangling the credit interbank market in the light of the CP dichotomy indicates that core banks started to hoard liquidity, while this effect was partially compensated for by more lending of peripheral banks. While overall interbank credit provision dropped tremendously, the market did not fully dry out since strong links could still be maintained.

2.3 Fitting Behavioral Models: An Actor-Based Approach to Link Formation

An alternative route on model estimation was taken by Finger and Lux (2014) who rather than using a prototype model for the network topology, estimated a micro-based model for elucidating the motivations of banks to engage in a credit relationship. To this end, they adopted the so-called actor-oriented network approach from sociology (SAOM model, Snijders, 1996). This model is based on a stochastic formulation of the objective functions driving agents' decisions to create new links or to delete existing links. The objective function is formulated in a very general form and might contain individual characteristics as well as any type of network structural information that might be conjectured to be of relevance (individual information like the degree, bilateral information such as prior existence of a link as well as overall structural statistics linking clustering coefficients and others). This approach, therefore, allows to gain insights in how far structural characteristics of a network influence agent's decisions and also in how far such features are purposefully aimed at by the agents. Parameters of such models are typically estimated by some method of moments algorithm. The SAOM approach has become widely popular in sociology over the last years and has been applied to a variety of settings where persistent links are important (friendship networks, counseling within various professional settings

³It need to be pointed out, that the CP architectures is based on different characteristics of a network than the class of scale free networks. It is, thus, not clear whether the sets of models defined in this way are mutually exclusive. For instance, since the power law of the degree distribution of scale-free networks gives rise to a number of nodes with much higher degrees than the average, these could be identified as the core of the network. Craig and von Peters (2014) and Fricke and Lux (2015a) have compared their results from estimating a CP model with Monte Carlo simulations of generating mechanisms for scale-free networks and both conclude that the identified core is likely not a spurious finding from a scale-free network topology.

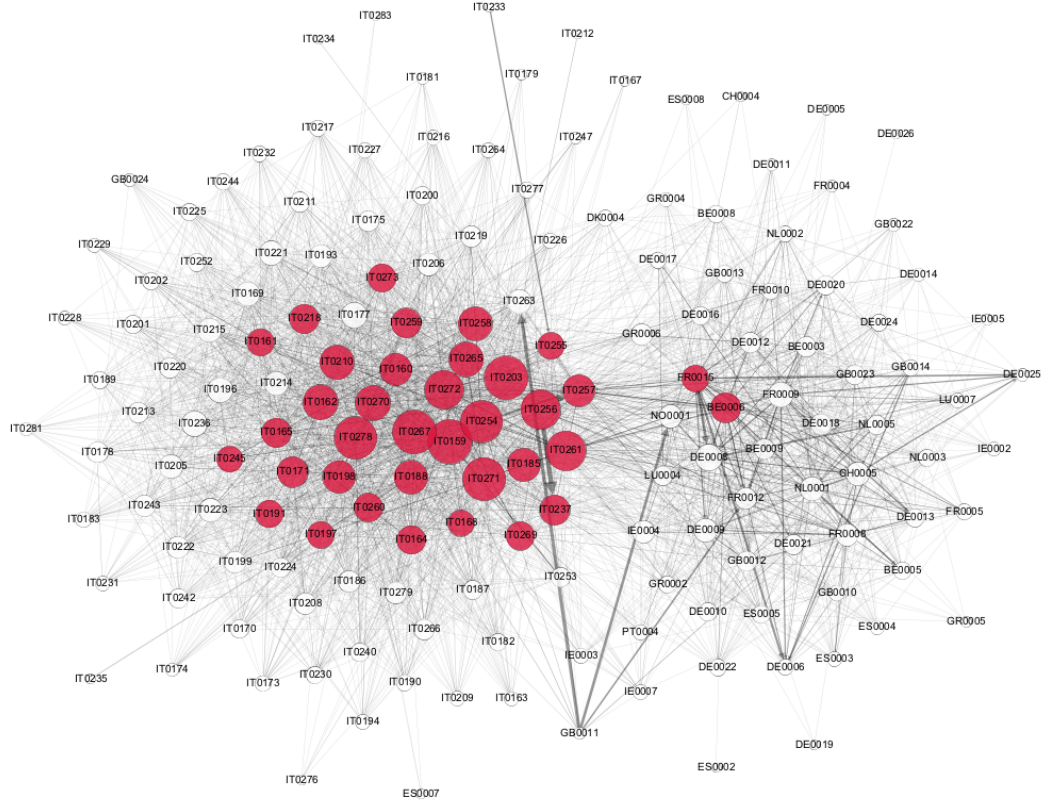


Figure 3: Data-driven identification of the ‘core’ of the interbank network. The underlying data are all transactions among Italian banks in the electronic trading platform e-MID over the first quarter of 1999. The ‘core’ banks are identified by red color, the peripheral ones by white circles. Only Italian banks are shown because the Italian and non-Italian banks constitute two separate clusters within their network with very few connections between both groups as seen in Fig. 1.

etc.). In our setting, the purported relevance of ‘relationship banking’ suggests that some similar non-trivial and non-random forces of network generation might be at work in the case of the interbank credit market. This approach is very close to estimating a discrete choice model with social interactions within a network structure (cf. Brock and Durlauf, 2011). The main difference is that discrete choice models in the econometrics literature assume that data are retrieved from a static equilibrium configuration, i.e. assuming that every agent correctly factors in the choice of all other agents in her decision making. In contrast, the SAOM approach considers out-of-equilibrium dynamics with agents adaptively adjusting their behavior to increase their utility (or whatever their objective function measures) and is typically used to study the evolution of social interactions over time. The approach is, therefore, close to the estimation of social interaction effects in evolving systems as studied in Lux (2009).

In the absence of prior work in a similar vein, Finger and Lux (2014) have used an objective function with a large number of candidate factors of influence. Estimating the model quarter by quarter, they again found very consistent results over time. The most salient effect was the influence of past trades on the prevalence of a link in the next quarter, again indicative of the relevance of existence of prior relationships and the development of trust between two partners. Surprisingly from an economic point of view, interest rates played a very minor role in link formation decision, with most interest-rate related variables turning out insignificant in most periods. With the start of the financial crisis, a few changes could be identified: First, large banks and those assigned to the ‘core’ by Fricke and Lux (2015a) became even more popular as counterparties than before (presumably because they were considered systemically relevant and, therefore, safe by others). Second, banks now apparently also took into account indirect network exposures via pertinent statistical measures and in this way reduced their indirect counterparty risk.

3 New Structural and Behavioral Models

3.1 An Interbank Network Model based on “Stylized Facts”

To provide a realistic image of the potential contagion dynamics within the banking systems of modern economies, network models of the interbank market need to be aligned to the “stylized facts”. As it had turned out from empirical studies of the interbank market, we have to particularly take into account: (i) the relative sparseness of existing links, (ii) the disassortative nature of link formation, (iii) the broad distribution of degrees (i.e., number of links), and (iv) the high persistence of established links.

Some of these features are in stark contrast to previous methods and models used in stress testing real-life banking systems and theoretical modeling of the interbank market. For instance, central banks have, in the absence of detailed information of interbank

credit links, mostly used a maximum entropy approach to implement the full matrix of interbank liabilities from aggregate balance sheet information (cf. Upper and Worms, 2004; Mistrulli, 2011). This approach, however, leads to a fully connected interbank system which is in obvious contrast to the typical structure of such a network in which only a small portion of all possible links does exist. Presumably, a fully connected system would have a much higher capacity of absorption of stress than a system with sparse connections. The first vintage of theoretical models, in contrast, has used entirely random link generating mechanisms (Nier et al., 2008) which is neither in harmony with the heterogeneity of the number of links nor the pronounced disassortative link formation (cf. Karimi and Raddant, 2016).

In Montagna and Lux (2015) a static network model has been developed that reproduces the above stylized facts (i) to (iii).⁴ Their model also reflects another important feature of the banking sector: The pronounced right-skewed size distribution of banks' balance sheets, cf. Bremus et al. (2013) for recent evidence. Following a long empirical legacy they draw bank sizes in the model from a Pareto distribution with a low value of the shape parameter. Heterogeneous bank sizes are also necessary to allow for different volumes of interbank credit traded by different banks.

It turns out that such a system is characterized by a much higher contagion potential after single defaults than an otherwise identical system with interbank credit modeled via maximum entropy or the Erdős-Renyi mechanism for generating random networks (cf. Fig. 4). Montagna and Lux (2014) develop an analytical approach for the analysis of the contagion dynamics within this model. Taking some information as given (balance sheet sizes and aggregate credit flows) and other data as unknown (the complete matrix of bilateral links), the expected number for defaults, capital losses and other quantities of interest can be computed via a numerical approximation to the temporal evolution of the multivariate density of banks' equity after an exogenous shock. Given that the model is based on well-known empirical findings for the structure of the interbank market, these forecasts should provide a relatively accurate perspective on possible system-wide repercussions of shocks. A very similar generating mechanism is used by Montagna and Kok (2013) to provide a realistic reconstruction of interbank credit between the 50 largest European banks. In this approach, aggregate balance sheet statistics are used as restrictions and the matrix of bilateral interbank credit is generated in a similar manner like in Montagna and Lux (2014,2015). This framework is then applied to study the systemwide repercussions of defaults of any one of the largest banks via Monte Carlo simulations.

⁴Anand et al. (2015) provide an alternative approach for generating sparse networks. Their algorithm is based upon information-theoretic principles and generates the network with minimum density under certain constraints. They report that their generating mechanism overestimates the effects of contagion.

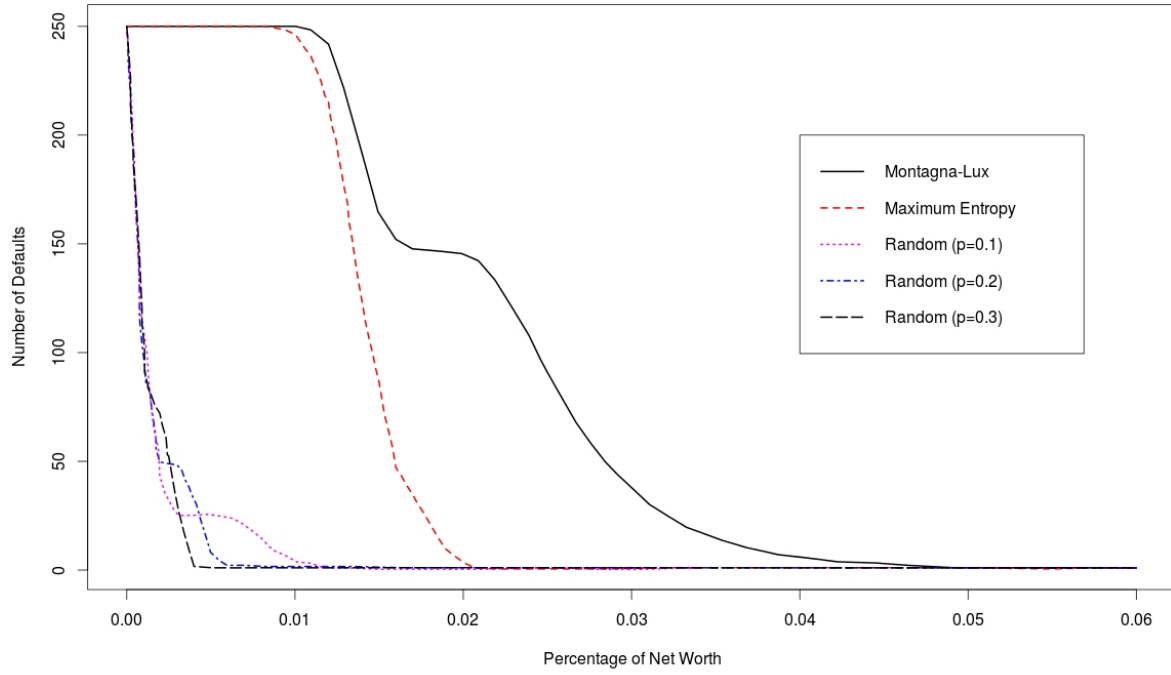


Figure 4: The number of subsequent failures after the default of the largest bank in the model of Montagna and Lux (2015), simulated with an overall number of 250 banks. The number of defaults is shown as a function of banks' equity ratio for different types of network topologies: a scale-free network with realistic properties corresponding to the “stylized facts”, networks designed according to the maximum entropy method and three random network scenarios with different probability for the existence of links (the random networks generated with $p = 0.1$ has the same (mean) density as in the scale free case). The more realistic model is much more prone to cascading failures than hypothetical settings with a random distribution of credit links or one with maximum dispersion.

3.2 Interaction between the Topology of Bank-Firm Loans and the Interbank Network

Montagna and Kok (2013) also add additional realistic layers of contagion to this model⁵. First, contagion in the interbank credit market is considered to have two aspects: propagation of defaults and loss of funding. The first aspect is the one that had been incorporated in previous literature: A default of one bank leads to losses of its creditor banks which – if their equity is not sufficient to absorb these losses – leads to further subsequent defaults. However, the defaulting banks might have extended interbank credit itself to other banks or might have standing credit lines to others who now suffer from a loss of funding opportunities. “Shock waves” might thus propagate in both directions of the creditor-borrower credit chain. In addition, banks might be exposed to similar exogenous risks through portfolio overlap, i.e. the holding of very similar portfolios. It is well-known that portfolios indeed have become more and more similar, not the least by application of identical methods of portfolio optimization provided by academic financial theory. If portfolios are synchronized, however, portfolio losses hit different banks equally and weaken the balance sheet structure of more than one bank at the same time. In addition, when losses on interbank credit or some assets of a bank’s portfolio occur, banks might be forced to liquidate other assets in order to conform to regulatory standards on minimum capital requirements and liquidity requirements. Uniform behavior under portfolio overlaps might then lead to large price drops of assets subject to fire sales and might in the aggregate exacerbate the initial liquidity problem.

Montagna and Kok (2013) study the joint effects of these different channels of contagion using empirical data on 50 large banks within the EU. This data consist of their balance sheets over a number of years plus information on interbank credit flows between the pertinent countries. This additional information provides a constraint to the distribution of links and volume in the interbank market, and simulations are conducted on the base of this information in a similar vein as in Montagna and Lux (2015). The most important insight provided by this study is that mostly different contagion channels interact in a mutually reinforcing way: with two or more channels active, the resulting cascade effects are larger than the sum of contagious defaults or losses from single channels.

Lux (2016) considers a closely related question: The additional effects brought about by joint exposure to the same counterparty risk in the market for loans to non-financial firms. For certain countries (Italy, Japan, Spain) almost complete data are available for the credit relationships between banks and non-financial firms. Again, stylized facts can be extracted from these data: (i) not unexpectedly, the mean number of loans taken per firm is smaller than the mean number for loans extended by banks; (ii) the distribution of

⁵Their result has also been featured in the European Central Bank’s Financial Stability report of 2013 (cf. Montagna et al., 2013).

links is much broader for banks than for firms; (iii) for both, banks and firms, the degree increases with size.

On the base of these findings, Lux (2016) sets up a stochastic model of link formation that can replicate these features. Surprisingly, although most small and medium-sized firms typically only have one or two creditor banks (and are, thus, minimally connected to the entire network), the network of bank-firm credit is characterized by a large connected component (cf. Fig. 5). This means that every actor (bank or firm) can be “reached” from any other actor by navigating through the links of the network. This also means that by its very nature, stress could virtually propagate throughout the entire system. Indeed, this is happening in a number of cases under simulated stress conditions: When considering individual firms as a source of an initial shock, the default of many firms remains without further aftereffects while for a small number, their default triggers a systemic crisis. Such a system can be characterized as being mostly stable, yet fragile (cf. Fig. 6). The distinct dichotomic outcome of ‘stress tests’ (no or very few aftereffects a system-wide collapse) is a very robust feature of this model. It is basically explained by the fact that potential aftereffects become more and more pronounced with every round of contagion defaults. Provided that all banks and firms have the same cushion (in terms of equity of banks and resilience to loss of funding for firms), a fall of one domino stone leads to so many negative repercussions for other units that it would virtually always lead to at least one additional failure. In the next round, the outreach of the shock becomes even larger so that again some weaker elements would be brought down. The maximum number of defaults happens indeed in the third and fourth round after the initial shock. A necessary condition for a systemic event is the existence of a *large connected component (LCC)*, i.e. almost all banks and firms can be reached by ‘traveling’ along their credit connections. The existence of such an LCC, however, appears to be guaranteed by the particular distribution of links we observe in empirical data.

Attempts to identify the “dangerous” firms ex-ante via their specific characteristics were largely unsuccessful: While there is a certain correlation between size as well as degree of a defaulting unit and the probability of a systemic crash, forecasts based on this correlation do not perform much better than random forecasts. One would, thus, have to know the exact network position of every actor to assess the risk inherent in this node. Indeed, taking into account information on the local structure of the network (the degrees and size of the immediately connected counterparties, degree and size of their counterparties forming the second ‘shell’ around the defaulting unit etc.) helps to improve the prediction of systemic events. In the absence of such detailed information, the model could give a benchmark for the necessary level of equity that makes the system safe against the disastrous cascades displayed on the right-hand side of Fig. 6. In the current toy model the necessary level of equity can exactly be determined, but it depends on how many additional channels of contagion are considered. E.g., it increases substantially

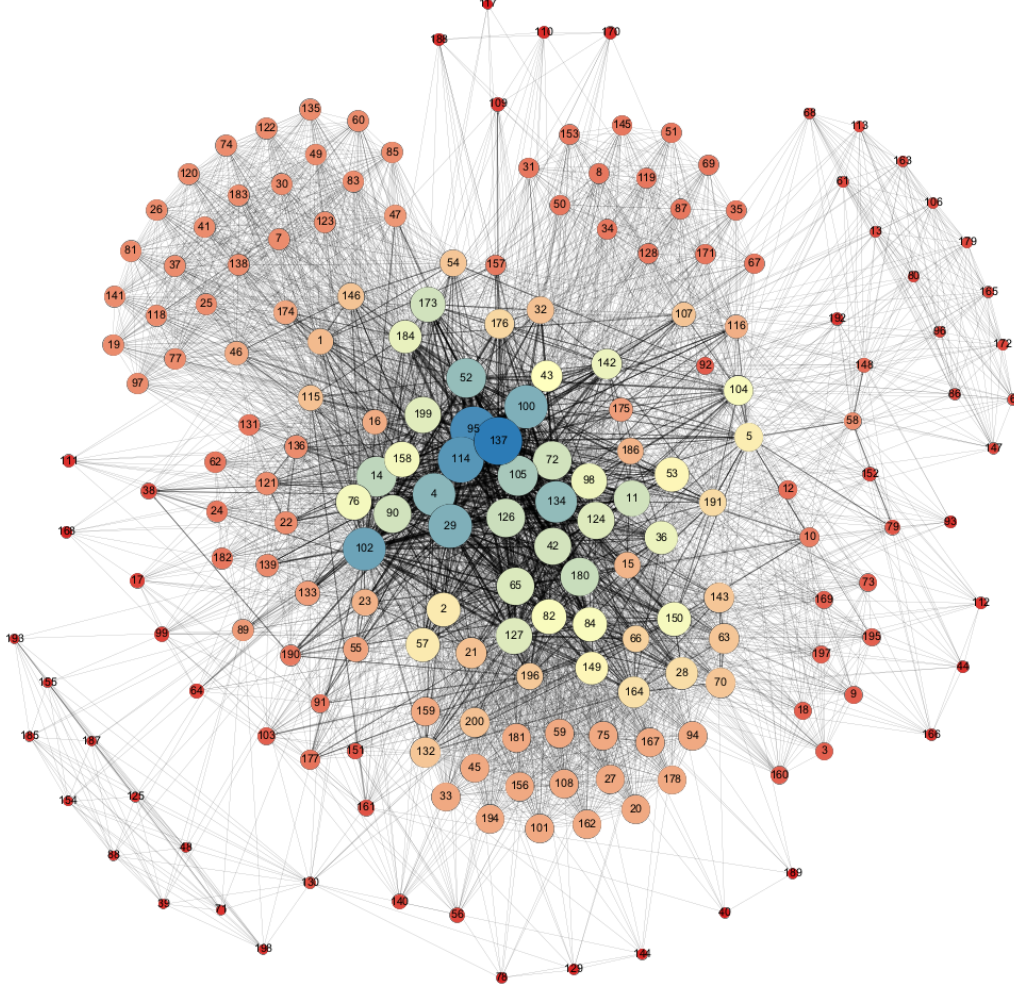


Figure 5: The network of links between firms obtained from their joint relationship to the same creditor bank (one-mode projection of the bipartite network) in a simulation of the model proposed in Lux (2016) with 20 banks and 200 firms. Although on average, the number of creditor banks per firm is small (equal to 2 in the present case), joint borrower relationships to the same bank create a fully connected network. Colors are used to enhance visibility.

if balance sheet effects due to asset price deflation are additionally integrated into the models.

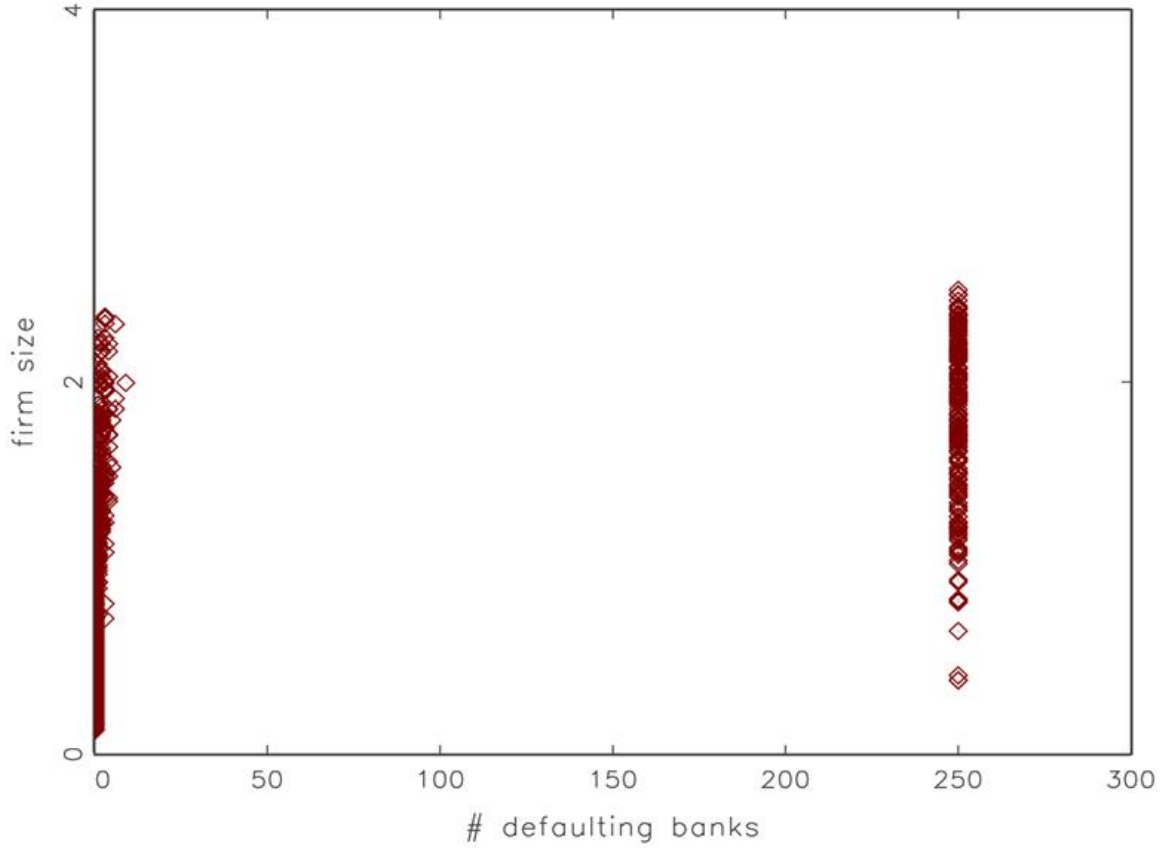
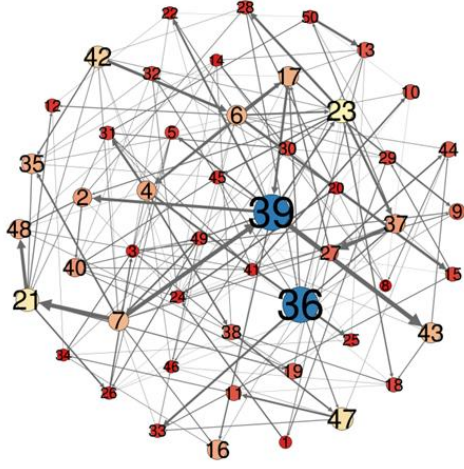


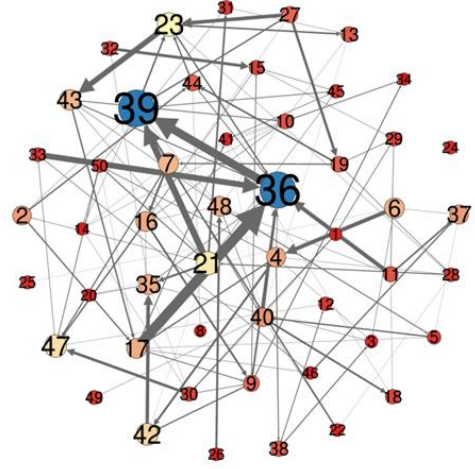
Figure 6: Number of bank defaults versus balance sheet size of defaulting firms in the model of firm-bank credit relationships of Lux (2016) with 250 banks and 10,000 firms. The figure reports the outcome of a ‘stress test’ in which the consequence of default of any one of the 10,000 non-financial firms is simulated and its subsequent effects through the connected bank-firm network are recorded. The right-hand side cluster of full system-wide breakdown covers only about 2 percent of all cases. The extent of contagious defaults seems almost independent of the size of the initially failing firm, but depends on its exact location within the network.

3.3 A Dynamic Model of Link Formation in the Banking Sector

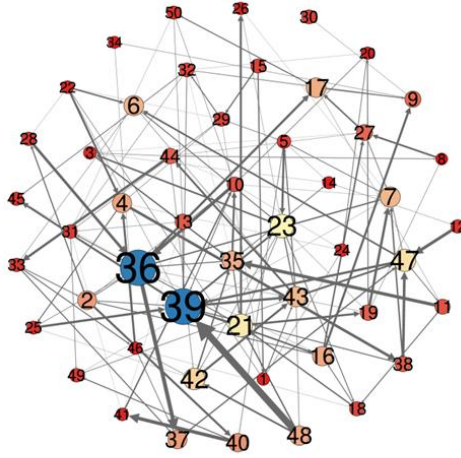
The objective of the previously surveyed contributions was to enlarge our understanding of the role and interaction of different contagion channels in a theoretical model that as closely as possible replicates empirical findings of the interbank market. However, such an analysis does not provide us with an understanding of the origin of the particular “stylized facts” of the interbank market which have simply been taken as given facts. To that purpose, a dynamic model has been designed in which banks are continuously affected by liquidity shocks (customers withdrawing or increasing their deposits). Since withdrawal of deposits in one bank mostly comes along with increases of deposits at some



(a)



(b)



(c)

Figure 7: Network images constructed from interbank loans in the dynamic model of Lux (2015); snapshots at times $t=100$ (a), 5000 (b) and $10,000$ (c) after random initialization. The direction of the arrows indicates credit extended from the lender to the borrower. The size of the nodes reflects their balance sheet size and the size of the links between them are proportional to their existing credit volumes in the particular period. As we observe, the network constructed from the interbank credit relations is relatively unstructured at the start of the simulation ($t=100$), but evolves into a more hierarchical structure in which a few banks have many links while the remaining ones only have few connections. Some banks can easily be spotted as the presumptive "core" banks that provide a certain number of other, mostly smaller banks with interbank loans. Colors are used to enhance visibility.

other banks (neglecting international aspects) overall liquidity of the banking system is assumed to be constant. As a consequence, while banks in any period have to balance their liquidity overhang or liquidity deficit via the interbank market, the necessary liquidity to be channeled via credit to those in need is always available within the system. The model proposed in Lux (2015) only uses a minimum of assumptions: (i) a fat-tailed size distribution of banks, (ii) mean-reverting and size-dependent liquidity shocks of banks (as found in empirical studies such as Hester and Pierce, 1975), and (iii) a trust-related choice of the preferred trading partner in the interbank market (i.e. relationship banking). Trust increases with the number of successful matches of two partners while it decreases if the preferred creditor does not accept an application for a credit (which might happen if his liquidity is also relatively low).

The emergence of a credit network is studied by initializing the system in a state without interbank credit and equal trust to all potential creditors. When liquidity shocks start to hit, the choice of the potential creditor a bank contacts is first completely random. Soon, however, lasting relationships emerge, i.e. links become persistent. These links are of a disassortative nature as larger banks typically can satisfy the liquidity needs of a number of smaller banks without jeopardizing their own liquidity position. Hence, core banks emerge with their respective periphery. Fig. 7 shows how the initially unstructured system develops into a more stratified, hierarchical one over time. While the details might change, the qualitative structure remains the same when after a phase of adjustment the system has reached a statistical equilibrium. The econometric analysis of the time series generated by this model reveals that it reproduces empirical findings to a large degree: (i) the network structure is disassortative and close to a core-periphery topology, (ii) links are persistent over time with a Jaccard index close to empirical figure, and (iii) banks show a higher dependency on their largest lender in the interbank market than on their largest borrower. While these features apply on average in a continuously changing market, they can be identical in Fig. 7 by the smaller number of links in 7b and 7c compared to the initial stage displayed in Fig. 7a. This thinning out comes along with the concentration on established relationships and the formation of a core-periphery structure. The emergence of strong lender-borrower relationships can also be inferred from the increasing thickness of the connecting lines between banks. Besides gaining an understanding of the emergence of the particular stylized fact of the interbank network, the model could also be used to study the dynamic effects of shocks causing structural adjustments in the network. While such a trust based structure might increase the resilience of the system, it might also imply that the built-up of a new network of relationships would take a long time once trust erodes due to particular circumstances (as it might have happened in 2007/08). For instance, shocks could lead to an overall loss of trust (as in 2007/08) and one could investigate, how long it takes to rebuild trust and what adjustments do occur in the mean time.

4 Conclusion

While almost no literature had existed on the internal connection within the financial crisis prior to the Great Financial Crisis, this literature has rapidly developed over the past few years. By now, most central banks have started to engage in collecting pertinent data and investigating those under a network perspective. While data availability is still more restricted than in other fields, a number of stylized facts could be identified that seems to be characteristic of the network topology of the financial sector. Unfortunately, these particular features also shape the reaction of this system to shocks, and mostly not in a very convenient way. As it is indicated by a number of models, the resulting structure appears ‘mostly stable, yet fragile’, i.e. it can absorb many shocks but might at the same time be triggered into disastrous spirals of cascading defaults by certain disturbances. To identify the candidate shocks that pave the way to disasters might not be easy as it requires an exact knowledge of the topology and the various contagion channels that propagate the shock waves throughout the system. In short, the regulator would have to know all details of the system and would have to be able to simulate the propagation of shocks in the real system as we did for our toy models to assess the risk of cascade effects. Stress tests initiated by monetary and supervision authorities have typically only considered the ?? of single institutions rather than stress propagation throughout the banking system. This is indeed what has been proposed in, e.g. Poledna and Thurner (2014), to internalize the network externalities that are caused by the propagation of risk through interbank linkage. Current regulations are less ambitious, but at least have already incorporated measures of connectivity into the distinction of systemically relevant financial institutions (Basel Committee, 2011). Given the multiplicity of contagion channels (of which not even all have been included into theoretical models so far) and the fast changes in balance sheet positions, an exact and timely mapping of network externalities appears, however, a most heroic undertaking. A more realistic perspective might be to infer from theoretical models what extent of cushion (minimum equity requirements, maximum leverage etc) would be required to make such a system sufficiently robust to make sure it is not dragged into an accelerating cascade of defaults by minor shocks.

References

- [1] Allen F. and Gale D. (2000), Financial contagion, *Journal of Political Economy*, 108, 1-34.
- [2] Anand, K., B. Craig and von Peter, G. (2015), Filling the blanks: Network structure and interbank contagion, *Quantitative Finance*, 15, 625-636.

- [3] Basel Committee on Banking Supervision (2011), Global Systemically Important Banks: Assessment Methodology and the Additional Loss Absorbency Requirement. Rules Text, Basel.
- [4] Borgatti, S.P. and Everett, M.G. (1999), Models of core/periphery structures, *Social Networks*, 21, 375-395.
- [5] Boss, M. et al. (2004), Network topology of the interbank market, *Quantitative Finance*, 4, 677-684.
- [6] Bremus, F., Buch, C., Russ, K. and Schnitzer, M., (2013), Big Banks and Macroeconomic Outcomes: Theory and Cross-Country Evidence of Granularity. NBER Working Paper No. 19093
- [7] Brock, W. and Durlauf, S. (2001), Discrete choice with social interactions, *The Review of Economic Studies*, 68, 235-260.
- [8] Cocco, J., Gomes, F. and Martins, N. (2009), Lending relationships in the interbank market, *Journal of Financial Intermediation*, 18, 24-48.
- [9] Craig, B. and von Peter, G. (2014), Interbank tiering and money center banks, *Journal of Financial Intermediation*, 23, 322-347.
- [10] De Masi, G., Iori, G. and Caldarelli, G. (2006), Fitness model for the Italian interbank money market, *Physical Review E*, 74, 066112.
- [11] Haldane, A. and May, R. (2011), Systemic risk in banking ecosystems, *Nature*, 469, 351-355.
- [12] Finger, K., Fricke, D. and Lux, T. (2013), Network analysis of the e-MID overnight money market: The informational value of different aggregation levels for intrinsic dynamic processes, *Computational Management Science*, 10(2-3), 187-211.
- [13] Finger, K. and Lux, T. (2014), Friendship between Banks: An Application of an Actor-Oriented Model of Network Formation on Interbank Credit Relations, Kiel Working Paper, 1916, Kiel Institute for the World Economy, Kiel: 42pp.
- [14] Fricke, D. (2012), Trading strategies in the overnight money market: correlations and clustering on the e-MID trading platform. *Physica A: Statistical Mechanics and its Applications*, 391(24), 6528-6542.
- [15] Fricke, D., Finger, K. and Lux, T. (2013), On Assortative and Disassortative Mixing Scale-Free Networks: The Case of Interbank Credit Networks. Kiel Working Paper, 1830, Kiel Institute for the World Economy, Kiel: 18pp.

- [16] 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.
- [17] 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*, 49, 1463-1495.
- [18] Hester, D. and Pierce, J. (1975), Bank Management and Portfolio Behavior. Yale University Press.
- [19] Illing, G (2012), Finanzmarktstabilität – die Notwendigkeit eines effizienten Regulierungsdesigns, Jahrbuch Normative und institutionelle Grundfragen der Ökonomik 11, 283- 306.
- [20] Karimi, F. and Raddant, M. (2016), Cascades in real interbank markets, *Computational Economics*, 47, 49-66.
- [21] Kindleberger, C.P. and Aliber R.Z. (2005), Manias, Panics and Crashes: A History of Financial Crises, Wiley Investment Classics Series, 39: 355pp.
- [22] Lux, T. (2009), Rational forecasts or social opinion dynamics? Identification of interaction effects in a business climate survey, *Journal of Economic Behavior & Organization*, 72, 638-655.
- [23] Lux, T. (2013), Effizienz und Stabilität von Finanzmärkten: Stehen wir vor einem Paradigmenwechsel?, Wirtschaftsdienst, 93(13): 16-22. (doi: 10.1007/s10273-013-1483-7).
- [24] Lux, T. (2016), A model of the topology of the bank-firm credit network and its role as channel of contagion, *Journal of Economic Dynamics and Control*, in press.
- [25] Lux, T. (2015), Emergence of a core-periphery structure in a simple dynamic model of the interbank market, *Journal of Economic Dynamics and Control*, 52, A11-A23.
- [26] Mistrulli, P. (2011), Assessing financial contagion in the interbank market: Maximum entropy versus observed interbank lending patterns, *Journal of Banking & Finance*, 35 (5), 1114-1127.
- [27] Montagna, M. and Kok, C. (2013), Multi-layered Interbank Model for Assessing Systemic Risk. Kiel Working Paper, 1873, Kiel Institute for the World Economy, Kiel: 55pp.

- [28] Montagna, M., Kok, C. and Halaj, G. (2013), Gauging the Effectiveness of Cross-Sectional Macro-Prudential Tools through the Lens of Interbank-Networks. *Financial Stability Report* 2013(2), European Central Bank, Frankfurt: 129-137.
- [29] Montagna, M. and Lux, T. (2014), Contagion Risk in the Interbank Market: A Probabilistic Approach to Cope with Incomplete Structural Information, Kiel Working Paper, 1937, Kiel Institute for the World Economy, Kiel: 39pp.
- [30] Montagna, M. and Lux, T. (2015), Hubs and Resilience: Towards more Realistic Models of Interbank Markets, in: I. Arribas and E. Tortosa-Ausina, eds., *Financial Integration and Financial Crisis: Some Recent Developments*, Bilbao, Fundación BBVA.
- [31] Nier, E., Yang, J., Yorulmazer, T. and Alentorn, A. (2007), Network models and financial stability, *Journal of Economic Dynamics and Control*, 31, 2066-2060.
- [32] Poledna, S. and Thurner, S. (2014), Elimination of Systemic Risk in Financial Networks by Means of a Systemic Risk Transaction Tax, *Working Paper*, Medical University of Vienna.
- [33] Raddant, M. (2014), Structure in the Italian overnight loan market, *Journal of International Money and Finance*, 41, 197-213.
- [34] Snijders, T. (1996), Stochastic actor-oriented models for network change, *Journal of Mathematical Sociology*, 21, 149-172.
- [35] Soramäki, K. et al. (2007), The topology of interbank payment flows, *Physica A*, 379, 317-333.
- [36] Stumpf, M. and Porter, M. (2012), Critical truths about power laws, *Science*, 335, 665-666.
- [37] 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.