Final report

Network Effects and Systemic Risk in the Banking Sector

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1. Motivation and Plan of the Project

The field of economics had been caught completely unprepared for the worldwide financial crisis that broke out in 2007/2008 and to some extend 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 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. 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 pointed an illusory picture of a financial sector that is governed only by rational behavior and in which phenomena like speculative bubbles, crashes and maniacs (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 Default 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. One of these is the role of the *network structure* of relationships within the banking sector. Only by 'mapping' and understanding this network structure it will be possible to understand the contagious spread of stress and design regulations to prevent a system-wide (systemic) crisis 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 contagion 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 goals of this project within this emerging literature have been the following:

- 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 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 section summarizes the results of the project concerning these different research questions.

2. Project Results

2.1. Empirical Research and the Structure of Development of Credit Relationships in the Banking Sector

2.1.1. Extracting "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 to the ubiquity of information on many other aspects of human activity, the financial sector is still the most opaque part of economic activity. 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 mostly only part of the pertinent banking sector. 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

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

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 necessary, at least for interbank credit in the overnight money market. Using daily or weekly data would provide snap shots 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). The most salient features of the e-MID data appeared to be the following:

- Sparseness of the network: only a small faction 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 period to the next which given the sparseness of links point strongly towards a non-random process of deliberate link formation,

- Disassortativity of link formation: typically two banks with a credit relationship assume very different positions within the overall network. In particular, the two 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.

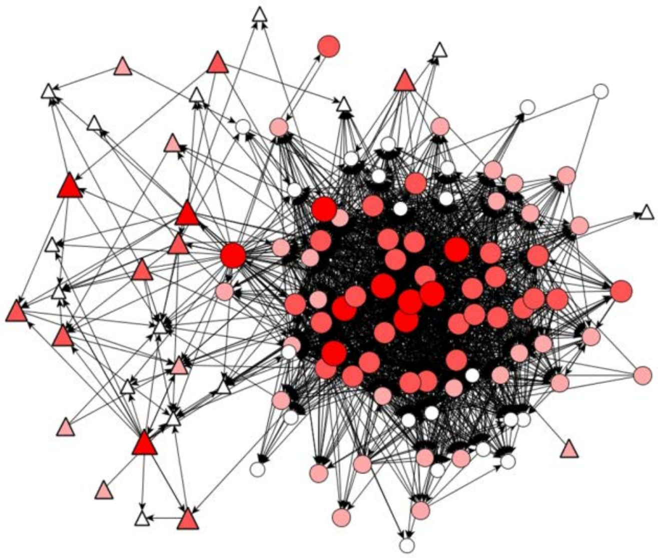


Fig. 1: Network image of the interbank credit transactions processed via the electronic trading system e-MID during the fourth quarter of 2010. Since e-MID is physically located in Italy, it is mostly used by Italian banks. The graphical representation, therefore, distinguishes between Italian banks (dots) and foreign banks (triangles). Size and brightness indicate volume of credit extended by the pertinent bank. The directed links capture the flow of credit from lenders to borrowers.

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). 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.

2.1.2. 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 Erdös-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 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. 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 demonstrated 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 practices have also been criticized in other areas of network applications). Finger et al. (2014) also show that the data under investigation deviate in other respects from those of 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.

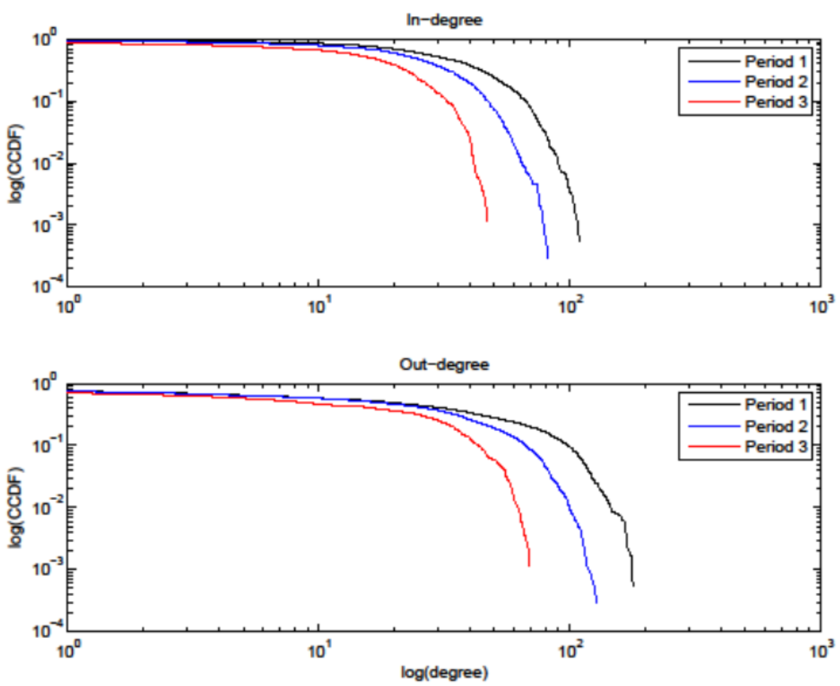


Fig. 2: Complementary cumulative distribution functions for the in-degrees (left), out-degrees (center), and total degrees (right) of banks participating in the e-MID electronic market at quarterly aggregation level. Three periods are distinguished because of structural breaks in the data. A power-law 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 (from Fricke and Lux, 2013).

Instead of physics-inspired models, a model 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). In its simplest form the discrete CP model provides a data-driven algorithm to identify the numbers and identity of the core members of a community characterized by a network. In so doing, one optimizes an objective function based on intuitive characteristics of a CP network (e.g. core members should be ideally fully connected among themselves, while the periphery should only be connected to the core, not within itself). 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. 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, banks might, for instance, be one of the core banks in terms of their 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, 2014).

The CP framework also allowed shedding some light on the intricate changes of behavior in the beginning of the financial crisis in 2008. 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.

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

An alternative route on model estimation was taken by Finger and Lux (2013) 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 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.

In the absence of prior work in a similar vein, Finger and Lux (2013) 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 (2014) became even more popular as counterparties than before (presumably because they were considered systemically relevant and, therefore, safe by others). Second, banks now 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 the empirical part of the project in conformity with other studies of other samples of interbank credit, 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, 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. 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 broad empirical degree distribution nor the pronounced disassortative link formation (cf. Karimi and Raddant, 2014)
In Montagna and Lux (2013) we develop a static network model that reproduces the above stylized facts (i) to (iii). We also found it important to reflect in the model another important feature of the banking sector: The pronounced right-skewed size distribution of banks’ balance sheets. Following a long empirical legacy we 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.

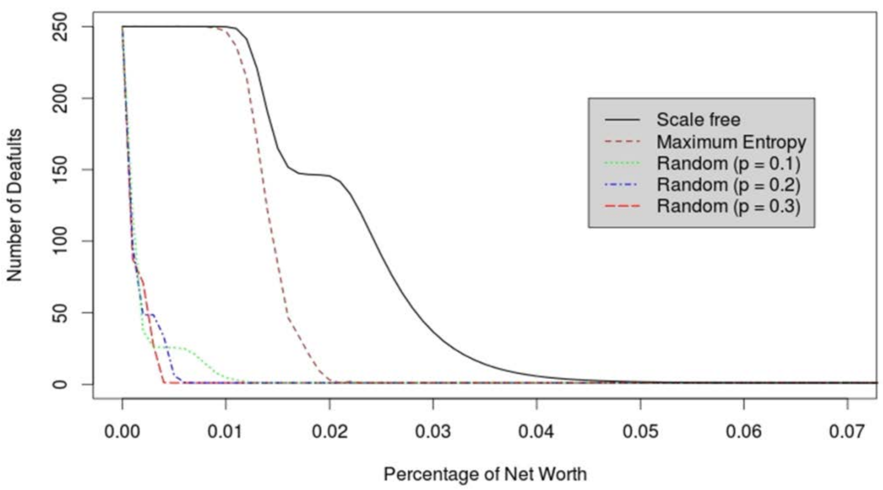


Fig. 3: The number of subsequent failures after the default of the largest bank in the model of Montagna and Lux (2013). The number of defaults is shown as a function of banks’ equity ratio for different types of network topologies: a scale-free network with realistic properties corresponding to the “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.

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 Erdös-Renyi mechanism for generating random networks (cf. Fig.3).
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.

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

Montagna and Kok (2013) add additional realistic layers of contagion to this model. 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 than 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 flowing 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 (2013). 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 (2014b) 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) complete data exist for the existence of 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 degree distribution of banks is much broader as well than that of firms; (iii) for both, banks and firms, the degree increases with size.

On the base of these findings, Lux (2014a) 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. 4). 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 to a systemic crisis. So the system is mostly stable, yet fragile (cf. Fig. 5).

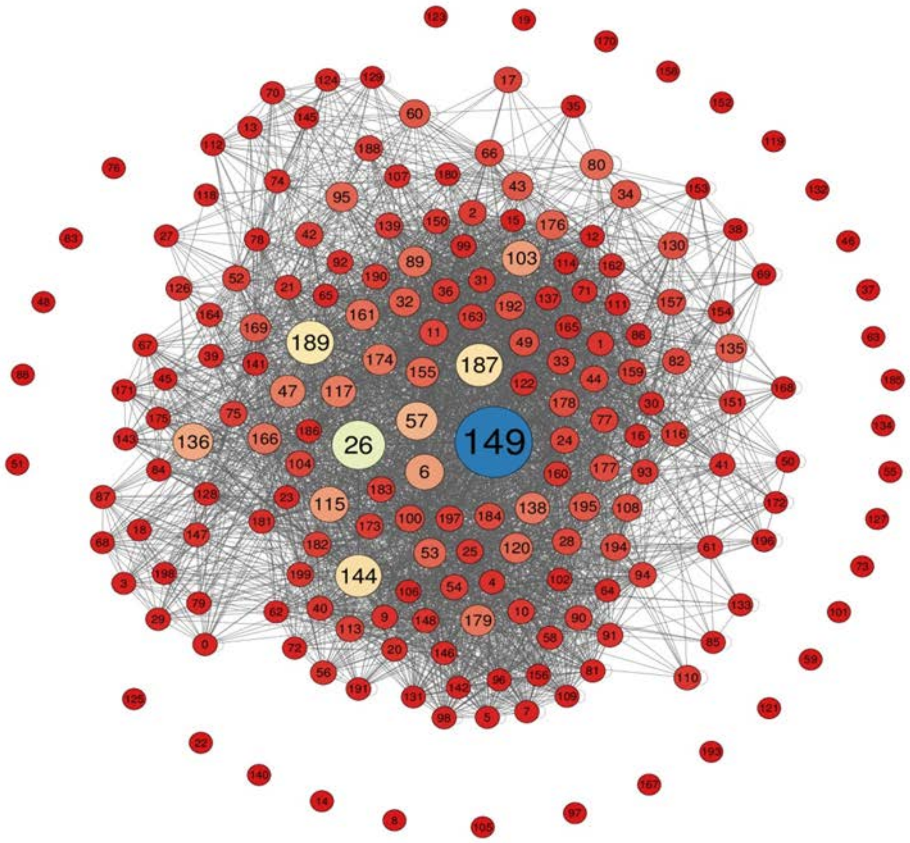


Fig. 4: The network of links between firms obtained from their joint relationship to the same creditor bank (one-mode projection of the bipartite network) in a simulation of the model proposed in Lux (2014a) with 20 banks and 200 firms. Although on average, the number of creditor banks per firm is small (equal to 2 in the present case), joint borrower relationships to the same bank create an almost fully connected networks (unconnected firms simply do not have any credit link).

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 and the probability of a systemic crash, forecasts based on this correlation do not perform 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. 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.5

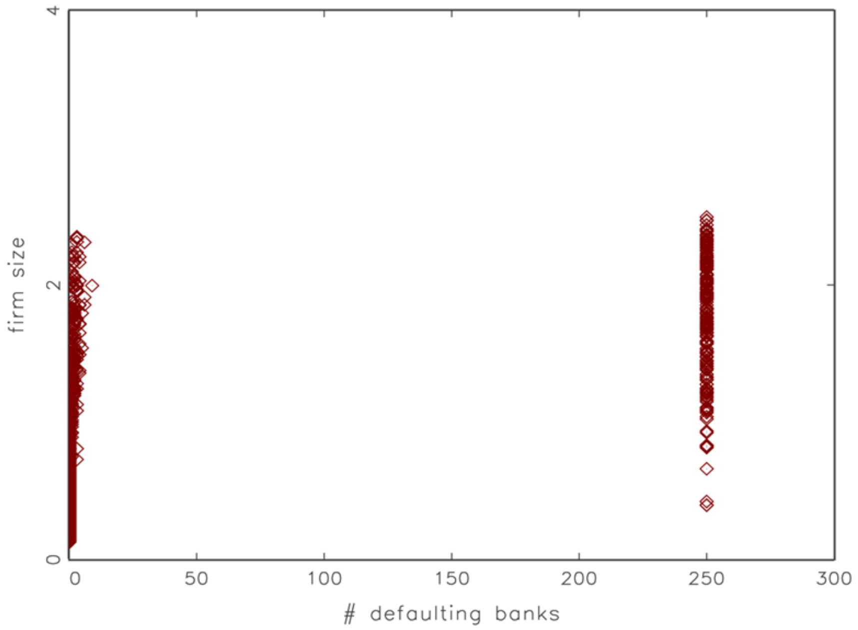
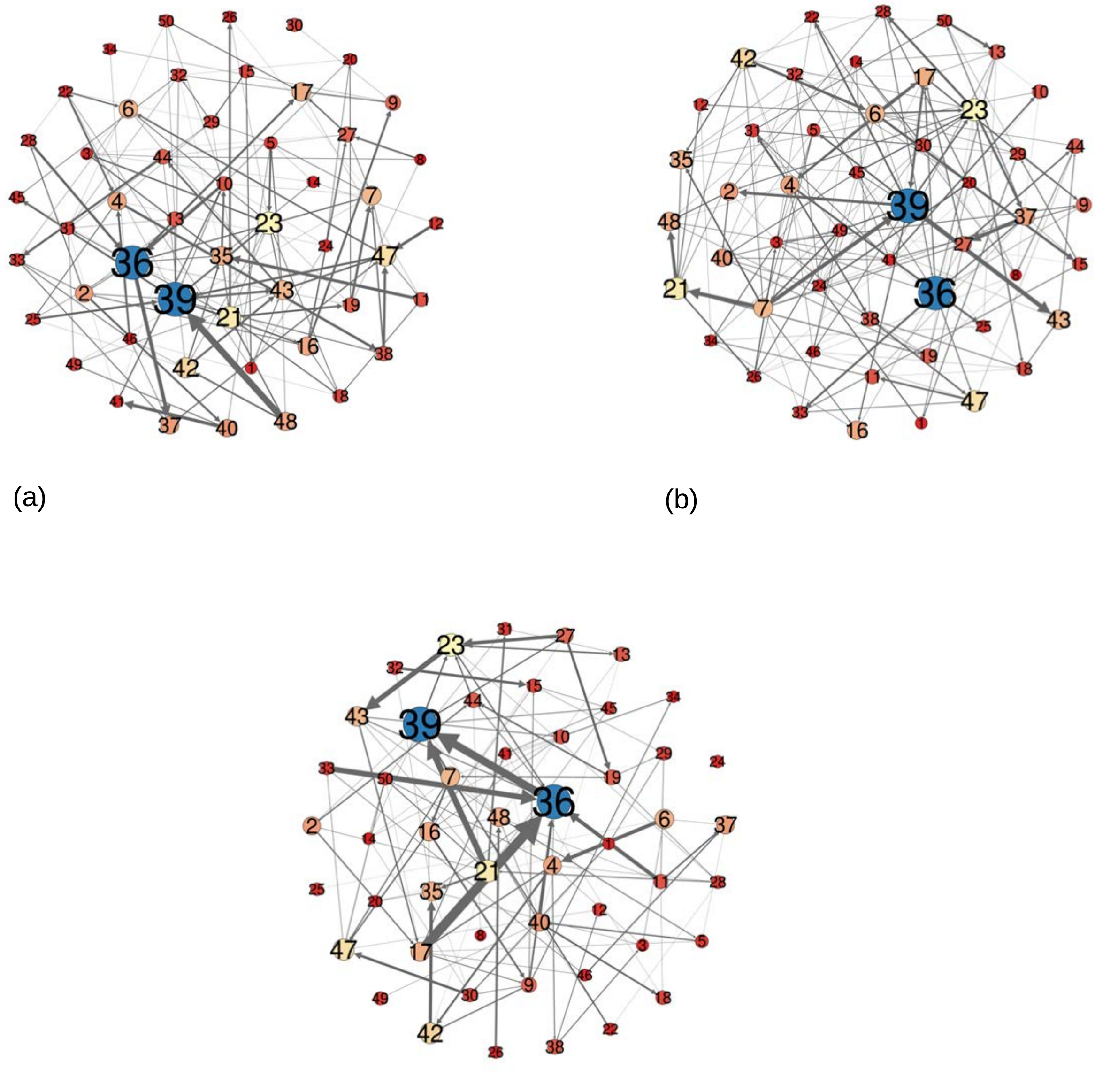


Fig. 5: Number of bank defaults versus balance sheet size of defaulting firms in the model of firm-bank credit relationships of Lux (2014a) with 250 banks and 10,000 firms. The right-hand side cluster of full system-wide breakdown covers only about 2 percent of all cases. The extent of contagious defaults 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

While the objective of the previously surveyed contributions was to enlarge our understanding of the role and interaction of different contagion channels, the final part of the project aimed at gaining an understanding of the origin of the particular “stylized facts” of the interbank market as it existed before the onset of the financial crisis and with reduced overall activity still exists today. To that purpose, a *dynamic* model has been designed in which banks are continuously affected by liquidity shocks (customers withdrawing or increasing their deposit shocks). Since withdrawal of deposits in one bank mostly comes along with increases of deposits at some other banks (neglecting international aspects) overall liquidity of the banking system is assumed to be constant. As a consequence, while banks at 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 (2014b) 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), 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).



(a) (b)

(c)

Fig. 6: Network images constructed from interbank loans in the dynamic model of Lux (2014b); snapshots at times t= 100(a), 5000(b) and 10,000(c). 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 who serve a certain number of other, mostly smaller banks with interbank loans.

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. 6 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. Besides gaining an understanding of the emergence of the particular stylized fact of interbank network, the model could also be used to study the dynamic effects of shocks causing structural adjustments in the network. 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. Dissemination and Outreach

The results of the project have been presented at various academic seminars, workshops and conferences, several times as invited keynote speeches. In addition, parts of this research have been presented at talks at the Banco de Españo, the Bundesbank and the European Central Bank and have been discussed during a one-day visit at the Monetary Authority of Singapore. Mattia Montagna combined his research on this project with a six month internship at the ECB's Financial Stability Assessment Division. Thomas Lux spent September 2013 as a visiting researcher at the same Division. The research report by Montagna and Kok (2013) has been published as part of the Financial Stability Report 2013 of the ECB (Financial Stability Report 2013(2), European Central Bank, Frankfurt: 129-137).

The general research topic of this project and the empirical and theoretical approaches developed in it will be further pursued within an FP7 Collaborative Project entitled “Financial Distortions and Macroeconomic Performance: Expectations, Constraints and Interaction of Agents” for which the Chair of Monetary Economics and International Finance at Kiel University serves as coordinator. The project partners consist of seven units at universities from six European countries, and the project is in general devoted to developing new approaches and models to be used for the foundation of monetary policy.
Three researchers of the project team have already completed and successfully defended their doctoral theses. A fourth thesis is currently under examination, and others are expected to follow in due time. In addition, a number of Master and Bachelor theses have been written on project-related topics. Daniel Fricke has moved as a post-doc to the Said Business School at Oxford University, where he continues this line of research. Mattia Montagna has accepted a position at the newly launched Single Supervisory Authority at the ECB (the new European banking supervision unit) where he is in charge of developing agent-based models of the network structure of the financial sector building upon his experience in this project and expanding this line of research for practical use.

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6. Publications:

6.1. Refereed research articles in journals and edited volumes

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