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JEL-Code: G21, G01, C35

Keywords: interbank market, network formation, financial crisis

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Friendship between Banks: An Application of the Actor-Oriented Model of Network Formation to Interbank Credit Relations☆

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Abstract

This paper investigates the driving forces behind banks' link formation in the interbank market by applying the stochastic actor oriented model (SAOM) developed in sociology. Our data consists of quarterly networks constructed from the transactions on an electronic platform (e-MID) over the period from 2001 to 2010. Estimating the model for the time before and after the global financial crisis (GFC) shows relatively similar behavior over the complete period. We find that past trades are a significant predictor of future credit relations which indicates a strong role for the formation of lasting relationships between banks. We also find strong importance of size-related characteristics, but little influence of past interest rates. The major changes found for the period after the onset of the financial crisis are that:(1) large banks and those identified as 'core' intermediaries became even more popular and (2) indirect counterparty risk appears to be more of a concern as indicated by a higher tendency to avoid indirect exposure via clustering effects.

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1. Introduction

In recent years the focus of banking regulation as well as the academic banking literature has started to shift from the analysis of the optimizing behavior of single banks to what is called a systemic perspective. Pertinent literature has started to study default patterns and the possibility of a system-wide breakdown (as it seemed immanent in 2007/08) from the viewpoint of a network approach to the structure of the financial system.[1]

The literature analysing the interbank market as a network has taken advantage of the fact that network related research has experienced a surge of interest recently in various scientific disciplines. The internet, friendship relations, cellular networks and ecosystems are just a few examples of complex systems investigated in terms of their network properties. The first applications of network theory to the banking system have been focusing on measures from the natural sciences describing the topology of the banking network to determine its general resilience or vulnerability in the presence of shocks. Examples are Inaoka *et al.* (2004) for the Japanese interbank market, Boss *et al.* (2006) for the Austrian banking sector, Soramäki *et al.* (2006) for the US Fedwire network, Bech *et al.* (2010) for the US Federal funds market and De Masi *et al.* (2006) and Iori *et al.* (2008) for the Italian interbank market. The most prominent findings of these studies are:(a) that degree distributions seem to follow a power law with coefficients between $2-3$, (b) the density of the network is relatively low,[2] (c) the networks show disassortative mixing with respect to their degree, (d) the average shortest path is very small (i.e. the networks exhibit a small world structure).

More recently, Craig and von Peter (2014) and Fricke and Lux (2014) show that the interbank network is close to a core-periphery structure, in the spirit of Borgatti and Everett (2000), for both German and Italian data of interbank credit relationships. The basic idea is that a few money-center banks (the core) are highly interconnected among themselves and act as intermediaries for the banks in the periphery. Cocco *et al.* (2009) and Affinito (2012) have also provided evidence for relational trading in interbank markets. Cocco *et al.* (2009) show for the Portuguese interbank market that banks pay lower interest rates on loans from banks they had frequently traded with in the past. Affinito (2012) also emphasizes long lasting trading relations and their positive effect during the global financial crisis (GFC)

[1] See e.g. Iori *et al.* (2006), Nier *et al.* (2007) and Haldane and May (2011).

[2] The density of a network is defined as the percentage of existing links to all possible links of a fully connected system.

in the Italian interbank market. Hence, their results support the prediction of Carlin *et al.* (2007) that cooperation among banks (traders) is an equilibrium outcome under repeated interaction. Iori *et al.* (2014) model an agent-based interbank market with relational trading and compare the generated networks with real world networks aggregated from transactions of the e-MID platform.

In this paper we approach the same topic from a complementary perspective: we use the stochastic actor-oriented model (SAOM) developed by Snijders (1996) to analyse the dynamics of the interbank network using longitudinal panel data. While the above studies use traditional statistical methods, the SAOM analyzes the evolution of the network from an actor point of view and so provides an avenue for identification of the driving forces behind banks decisions about their counterparties in the interbank market. In the last few years this model has been heavily used in sociology, but also in neighbouring fields.[3] However, to our best knowledge the SAOM has never been used in the economics literature.

The data set used comprises all Euro denominated overnight transactions by Italian banks in the electronic market for interbank deposits (e-MID) from 2001 to 2010 aggregated into quarterly networks. Since the test of Lospinoso *et. al* (2011) detects time heterogeneity for almost all effects the model will first be estimated separately for each quarterly aggregate. Afterwards the two-step multilevel approach proposed by Snijders and Baerveldt (2003) is applied to assess the overall significance of the hypothetical effects for the complete sample and the subperiods before and after the GFC.

In our version of the SAOM model we apply a large number of network-related effects, actor-specific and dyadic variables as potential determinants of agents' link formation. Overall the behaviour of banks appears relatively robust in almost all respects over the complete sample period and this stability should have contributed to the relative resilience of the interbank market during the GFC. The most salient result of our analysis is that banks heavily rely on lasting relations, although an electronic platform like the e-MID reduces the direct costs to trade with 'new' counterparties practically to zero. Only before the GFC (where the spreads were very small[4]) do we find

[3] See for example Checkley and Steglich (2007) for the impact of the mobility of managers on venture capital firms and Johnson *et al.* (2009) for an analysis of seasonal changes of an ecosystem.

[4] See Raddant (2012).

that the behavior of banks was slightly influenced by the average interest rates of their counterparty. Two additional changes are observed after the onset of the GFC: (1) larger banks and 'core' (as identified by Fricke and Lux, 2014) banks becoming more popular and (2) banks avoiding intermediate relations more than before. Both aspects indicate that counterparty risk has become a more important factor. The first aspect might support the 'to big to fail' and 'to interconnected to fail' argument in case of the size and core variables, respectively.

In general, banks' choices of counterparties in the interbank credit market seem to favour hierarchical ordering on the local (no cycles) and global level (degree distributions). Moreover, mutuality does not simply strengthen a relation, since only the creation of a mutual relation is valued by banks and not the maintenance of an existing one. This is in stark contrast to earlier findings in other applications of the SAOM regarding human relations, where enduring mutual relations with 'investments' already undertaken from both sides are extremely unlikely to be terminated. However, we have to bear in mind that a credit contract is in itself already a mutual contract so that the motivations of our actors is certainly different from that of humans forming friendships. The diverging findings on mutuality might, thus, be interpreted as a preference for borrowing to former creditors (to whom some link already exists) but there is no point for banks in keeping up intentionally credit relationships in both directions over time. Furthermore, while we find a high level of the directed clustering coefficient for the complete network we do not observe that banks would put any value on such triadic intermediate relations in our disaggregate analysis. Hence, it appears that the high clustering statistics emerges unintendedly from the interaction of the individual banks. Another interesting aspect is that we find support for the relevance of the core-periphery distinction since the binary categorisation of banks along the results of Fricke and Lux (2014) enters as a significant effect although the model also controls for the size of banks and many other effects capturing hierarchical aspects of the network.

The rest of the paper is organized as follows. Section 2 introduces the e-MID data, provides details on how to aggregate trades into an interbank network, and defines basic network terminology and the covariates used. In section 3 the general specification of the SAOM, the implemented effects and the estimation approach are explained. In section 4 the results for the Italian interbank network are presented and discussed.[5] Section 5 contains

[5]The estimation results for every single period and all specifications mentioned are

final remarks and conclusions.

2. Data Set and Network Construction

The Italian e-MID market is the only existing electronic broker market for interbank deposits, while all other segments of interbank lending worldwide are over-the-counter. Detailed information on the latter type is typically unavailable to regulators and researchers. Publications of the European Central Bank stated repeatedly in recent years that the e-MID data should be representative for the dynamics of the complete money market, so that one might expect to obtain representative results on interbank trading activity from this data set.[6] The data set contains tick-by-tick transaction data on Euro denominated interbank deposits from 1999-2010. Only overnight deposits, which account for more than 80% of all trades, are considered in the following.[7]

The 353 different banks that were active during this time span are known to us only by their unique ID number used in the data set. We omit non-Italian banks trading in the e-MID platform because they were mostly only trading within their relatively small group and their number among the e-MID participants showed large variability over time (cf. Finger *et al.*, 2013). Therefore, only the active 255 Italian banks are considered. Only the transactions from 2001-2010 are used in the empirical estimation, since fluctuations of banks entering and leaving the e-MID platform have been very high prior to this period. The market is quote driven and these quotes include bank-ID, the interest rate offered and the identification as sell or buy quote. These characteristics are normally visible to all participating banks. It is possible to engage in bilateral trade, where a quote is only seen by a pre-specified counterparty, but this happens very rarely. The quoting bank in any case gets to know the aggressor before the trade is executed.

Before explaining how to construct our observed networks from this data set we introduce some basic network terminology. A network consists of N nodes (order) and S links (size). It is represented as a $N \times N$ adjacency matrix (AM) x, where the element x_{ij} provides information on whether credit has been extended from bank i to bank j in the current period or not. In our application of the SAOM to interbank data, we only consider

available upon request from the corresponding author.

[6] See e.g. Beaupain and Durré (2011, 2012).

[7] Maturities up to 1 year and transactions in Dollars, Sterling and Zlotys are possible.

a binary adjacency matrix (i.e. $x_{ij} \in \{0, 1\}$) while in other studies we have also used weighted adjacency matrices containing information on the aggregated size of interbank loans. The network is directed and so x_{ij} does not need to be equal to x_{ji}, leading to an asymmetric adjacency matrix. The diagonal elements x_{ii} are zero by assumption, since banks are not trading with themselves. The sum of outgoing links $\sum_{j=1}^{N} x_{ij}$ is the outdegree of actor i and the sum of incoming links $\sum_{j=1}^{N} x_{ji}$ defines the indegree of actor i.

The next step is to aggregate single trades into interbank networks. To transform the transactions into a network it is necessary to aggregate them over a specified period. In our main application the data is aggregated on a quarterly basis, leading to 40 observations.[8] The most common approach in the literature is to use networks estimated from daily data, but we argue that for the present analysis a longer aggregation period is needed, since daily networks are too noisy and many existing links will simply not be activated on any particular day. Finger *et al.* (2013) scrutinize the question of the 'appropriate' aggregation period and show that most network statistics are stable and saturate around the quarterly level. Table 1 displays basic statistics of our quarterly networks which will be defined and referred to in the presentation of the empirical model and the estimation results.

Before turning to the SAOM we introduce the covariates implemented as exogenous variables in the model. Note that since the banks' identity is unknown to us all covariates are derived from the underlying data set of interbank lending and its network representation itself. In general there exist two types of covariates: actor specific covariates and dyadic covariates. All covariates are centered by subtracting the mean prior to the estimation process. Inactive banks in case of actor covariates and inactive dyads in case of dyadic covariates are left out of this procedure and are assigned a zero (the new average). Hence, they will not affect the results and the interpretation of all effects.

The Q actor covariates v_{im}^{q} are specific characteristics of each actor and are stored in vectors of length N (number of active banks), where q indicates the corresponding covariate, i the actor and m the period. The values are allowed to change over time. In our model we consider four actor covariates:(1) a proxy for the size of each bank v_{im}^{1} is calculated as a categorical variable using the total transaction volume each bank was in-

[8]Only 37 of them are used in the application, since we use the trading activity of the last year as a covariate.

volved in during the current quarter. The banks are classified into quintiles $v^1_{im} = \{1, 2, 3, 4, 5\}$, where the 20% of banks with the highest volume are attributed size 5 etc.[9],(2) core is a dummy variable v^2_{im} and takes the value 1 if the bank had been found to be in the core in the pertinent period according to Fricke and Lux (2014) and zero otherwise,(3) the lending rate v^3_{im} is calculated as the difference between the volume weighted average interest rate that banks received for their loans and the mean over all active banks which have lent money in this quarter,(4) analogous, the borrowing rate v^4_{im} is calculated as the volume weighted average interest rate from all transactions in which i had borrowed money minus the mean over all borrowers.

Dyadic covariates w^d_{ijm} measure characteristics specific for each ordered pair $(i{,}j)$ of banks, where d is the index of the dyadic covariate and m the period. They are stored in non symmetric $(N * N)$ matrices. The first dyadic covariate, called past trades, is the square root of the number of interbank loans extended from i to j during the last year

$$w^1_{ijm} = \sqrt{B_{ij}} - \frac{1}{(N-1)^2} \sum_{i=1}^{N} \sum_{\substack{j=1 \\ j \neq i}}^{N} \sqrt{B_{ij}}. \tag{1}$$

It proxies the intensity of the directed relationship in the past and subtracting the average over all potential links (second term) centers the covariate. Using the square root rather than the raw numbers is motivated by the right skewness of the distribution of the numbers of transactions. The second is the relative deviation of the volume weighted average interest rate between each ordered pair from the volume weighted average among all transactions during the last quarter:

$$w^2_{ijm} = \frac{\sum_{c=1}^{C_{ij}} a_c i_c / \sum_{c=1}^{C_{ij}} a_c}{\sum_{d=1}^{D} a_d i_d / \sum_{d=1}^{D} a_d} - 1/P \sum_{i=1}^{N} \sum_{\substack{j=1 \\ j \neq i}}^{N} \frac{\sum_{c=1}^{C_{ij}} a_c i_c / \sum_{c=1}^{C_{ij}} a_c}{\sum_{d=1}^{D} a_d i_d / \sum_{d=1}^{D} a_d} \tag{2}$$

where a is volume and i the interest rate for each directed transaction, C_{ij} and D are the number of transactions between the ordered pair $(i{,}j)$ and the total number of all transactions during the last quarter and P is the number of directed pairs of banks which traded during the last quarter. The second

[9]After the centering procedure the values change to $v^1_{im} = \{-2, -1, 0, 1, 2\}$.

term is centering the covariate by subtracting the average of the first term over all active dyads. We call this variable the past rate. It will allow us to measure whether banks prefer to lend to other banks if their previously agreed upon interest rates were relatively high or low. In addition to these actor specific and dyadic covariates, the model will include a number of structural network characteristics in order to assess in how far banks' link formation is tending towards the creation of a particular type of network configuration (see below).

3. The Stochastic Actor Oriented Model of Network Formation

The SAOM proposed by Snijders (1996) is a flexible approach to model and analyze longitudinal network data.[10] The actors are supposed to have full knowledge of the present network including all actors, relations and covariates. This is the case for the e-MID market, since all banks participating have access in real time to at least all the information we use in our analysis. Furthermore, the model assumes that links have the tendency to endure over time which is also crucial for the convergence of the estimation algorithm. Snijders *et al.* (2010b) articulate a rule of thumb that a Jaccard index of above .3 indicates a stable link structure, while our observed networks have on average a Jaccard Index of .54 (cf. Table 1).[11] The evolution is considered to be the result of purposeful actions by independent actors having control of their outgoing links. Certainly, the lending bank has full control of its transactions and should follow a distinct rationale when deciding about its lending relationships. Finally, the actor is supposed to

[10]It belongs to the agent-based family of models, but since Snijders chose the term actor we stick to this terminology as well. The SAOM approach has some similarity to discrete choice models with social interactions developed in economics (cf. Brock and Durlauf, 2001). One of the main differences is, however, that the latter typically assumes an equilibrium configuration, i.e. every agent takes correctly into account the social influence of himself and all other agents on their peers and the system of interacting choices is observed in a equilibrium of social interactions under rational expectations. With its non-equilibrium setting, the SAOM also bears some resemblance to the type of models of social interactions pioneered by Weidlich and Haag (1983).

[11]The Jaccard index $J = \frac{S_{11}}{S_{01}+S_{10}+S_{11}}$ is used to quantify the similarity of two sample sets, where S_{ab} counts the number of relations having status $x_{ij} = a$ at the first instance and $x_{ij} = b$ at the second. It measures the surviving links as a fraction of the links established at any of two adjacent points in time. See Finger *et al.* (2013.) for Jaccard indices for the data under scrutiny measured over different aggregation frequencies.

evaluate the network structure and try to obtain an advantageous configuration based on the current state of the network, while modifying its outgoing links. Since banks should try to maximize some kind of objective function by managing their interbank lending operations this seems not restrictive in our case. Hence,our interbank data are in conformity with the basic setting for the application of the SAOM, a network structure undergoing changes in time trough deliberate formation of new links, and abortion of existing ones.

3.1. Model Specification

A continuous time Markov setting with time parameter $t \in T$ is used and so the actor is solely considering the current state of the network during his decision making process. The M observed networks are embedded in this continuous set of time $T = [t_1, t_M]$, where the unobserved changes take place in between two observations. In our case the network observations are proxied by quarterly aggregated transactions.[12] The N banks which were active during at least two subsequent observations form the set of actors $\Gamma = N_1, ..., N_M$. Since we observe entry in and exit from the e-MID over time, the number of actors at time m, N_m, are the subsets of those banks that have been operating in the electronic platform at both t_m and t_{m+1}.[13] Since the number of banks per quarter is not of much relevance, we will simply drop the time subscript in the following. All possible network configurations constitute the space of potential outcomes.[14] The so-called rate function (RF) and the objective function (OF) together determine the complete model.

The RF $\lambda_i(\rho)$ indicates how often a single bank i will on average consider to change one of its outgoing links (inaction possible) in between two observations $t_m \leq t < t_{m+1}$. Similarly like in other models of social interaction (cf. Lux, 2009), it will be assumed that each actor becomes active with a Poisson rate λ_i that might be varying with time or depending on exogenous factors. The conditional independence of the actors implies that

[12] This is called event data and is e.g. also applied when e-mails are used to proxy human relations.

[13] While such movements in and out of the network could be incorporated in the SAOM, we are not covering them in our behavioral modelling. This is because entry and exit are basically consequences of mergers and acquisitions, and therefore are driven by a rationale outside the scope of our model.

[14] There exist $2^{N(N-1)}$ different outcomes defined by whether a link exists or not for each ordered pair of actors.

at each point in time t, the time until the next change by any actor follows a negative exponential distribution with parameter $\lambda_+ = \sum_{i=1}^{n} \lambda_i$. Hence, the expected waiting time is $1/\lambda_+$ and the probability for actor i to be the next actor to change its network position is λ_i/λ_+. A first step to allow heterogeneity in the rate function is to let the rate of change differ in between the periods ρ_m. The rate could also depend on the actor itself due to actor covariates. Additional parameters would be needed to quantify the strength of the influence of these actor covariates on the activation frequency of agents. Following Snijders and van Duijn (1997) we model the influence of actor covariates by an exponential function

$$\lambda_i(\rho_m, \alpha) = \rho_m \exp \sum_{e=1}^{E} \alpha_e s_{im}^e, \tag{3}$$

to ensure non-negative rates of change for all actors, where s_{im}^e are the E actor covariates as defined for the observation m of the network at time t_m. We will consider only the size of bank i, i.e. v_{im}^1 as defined in sec. 2, as covariate in the rate function, with α_e the corresponding coefficient measuring its influence. Note that $E \neq Q$, because not all covariates are implemented in the RF.

The objective function (OF) determining the incremental changes of the actor's network position upon activation is formalized as:

$$o_i(\beta, x, j) = f_i(\beta, x, j) + u_i(x, j). \tag{4}$$

It indicates the preference of bank i when it is chosen by the RF and determines its action, where x and j denote the dependence on the current state of the network and the counterparty, respectively. It is defined as the sum of the so-called evaluation function (EVF) plus a random element u_i, where β is the vector of parameters of the effects included in the EVF. The EVF expresses the satisfaction or utility of actor i depending on the current network. Possible changes are evaluated in terms of their potential to increase or decrease this level of satisfaction. Some effects focus exclusively on the contribution of already existing links and, hence, measure the change of utility between maintaining an established credit relation or dissolving it. This allows to evaluate whether continuation of a relationship has value by itself on top of contributing to the configuration of connections favored by the agent.[15] The random term in the OF represents the idiosyncratic part

[15]In the sociology literature these effects are incorporated in an additional component

of the actor's preference that is not covered by the EVF. It is assumed to follow a Gumbel distribution with mean 0 and scale parameter 1.[16] These random variables are assumed to be independent and identically distributed for all i, j, x and t_m. The new network configuration after the change of an element x_{ij} is denoted by $x(i \rightsquigarrow j)$. The chosen actor faces, therefore, a discrete choice problem with N possibilities (linking to or dissolving the link to the $N-1$ different j and the option of inactivity denoted by $x(i \rightsquigarrow i)$). The probabilities for the new states, following Maddala (1983), are given by the multinomial logit expression

$$p_{ij}(\beta, x, j) = \frac{\exp(o_i(x(i \rightsquigarrow j))}{\sum_{n=1}^{N} \exp(o_i(x(i \rightsquigarrow n))}. \tag{5}$$

This decision making process maximizes the short-term utility of the actor and can be considered as a form of myopic optimization. Hence, the actor is not taking the future ramifications of their own action into account or trying to anticipate actions of others. The EVF is modeled as the sum of a number of effects

$$f_i(\beta, x, j) = \sum_{k=1}^{K} \beta_k s_{ik}, \tag{6}$$

where the weights β_k are statistical parameters indicating the strength of the corresponding effect s_{ik}, and K is the number of effects. These effects are the substantive part of the model and represent possibly meaningful aspects of the network from the viewpoint of the actor. There are two main categories of effects:(1) structural effects depending solely on the network, which can be regarded as endogenous network effects (e.g. reciprocity) and (2) exogenous effects which depend on covariates.

The OF and the RF together define the transition probabilities of the Markov process

$$q_{ij} = \lambda_i(\rho, \alpha) p_{ij}(\beta, x, j). \tag{7}$$

To sum up, the RF determines how frequently agents are chosen and the OF defines which action they will undertake with a certain probability to maximize their short-term utility obtained by the network.

of the OF called gratification function. However, since only one such effect is implemented in our model we neglect this distinction for the sake of economy in our presentation.

[16]This is the standard assumption for the error term in random utility models, e.g. Maddala (1983).

Statistic	mean	sd	min	max
Distance	1520.44	434.39	818	2735
Jaccard Index	.54	.03	.47	.60
Active Banks	108.97	13.62	90	139
Links	2535.92	725.81	1449	4062
Density	.21	.02	.17	.25
Mutual Links	520.50	195.49	146	870
Reciprocity	.20	.04	.10	.29
CC^1	.58	.02	.52	.61
CC^2	.15	.04	.07	.24

Table 1: Descriptive statistics calculated for the 36 quarters from 2002-2010.

3.2. Network Effects

The SAOM had been proposed in the first place as a tool to analyze human relationships like friendship networks. In sociology, it is mostly applied to test specific hypothesis (i.e. one or two parameters) and the other effects are implemented as controls to specify the 'complete' model. Since this is the first application of a SAOM to interbank data,we will allow for a relatively large number of plausible effects suggested both by the interbank scenario and the former SAOM literature.

The only effect implemented in the flexible part of the rate function is the size v^1_{im} of the banks. In the form of a categorised variable explained in section 2. The effect is included in the RF according to Eq. (3):

$$\lambda_i(\rho_m, \alpha) = \rho_m \exp(\alpha v^1_{im}), \tag{8}$$

and measures if banks of different size classes are more/less active in creating and ending lending relations.

The objective function is the centrepiece of the model and determines which links are altered by actor i. It consists of the EVF and all implemented effects are summarized in Table 2. In the following the terms lending relation or borrowing relation are used as synonyms for outgoing links and incoming links to make the economic implications more transparent. The *outdegree* or *density* effect is defined by the outgoing links of (bank)

effect	category
density (outdegree)	structural
reciprocity	structural
reciprocity persistence	structural
transitive triplets	structural
3-cycles	structural
indegree popularity (sqrt)	structural
outdegree activity (sqrt)	structural
past trades	dyadic covariate
past rates	dyadic covariate
covariate popularity	actor covariate
covariate activity	actor covariate
covariate similarity	actor covariate

Table 2: The effects used in the objective function. The columns state the name of the effect and the category. For all four actor covariates (size, core, lending rate, borrowing rate) the last three effects are implemented.

i[17]

$$s_{i1} = x_{i+} = \sum_{\substack{j=1 \\ j \neq i}}^{n} x_{ij}, \tag{9}$$

i.e. the number of banks i is lending money to. Note that since credit relationships of a bank with itself are never meaningful we will drop $j \neq i$ in the following.[18] Eq. 9 represents the basic tendency to establish links. In a very simple model with only the *density* effect a positive parameter would indicate that banks prefer creating new links over ending existing ones and hence would attempt to attract more and more customers in the interbank credit market.[19] We would expect certain limitations of capacity to be present in such a scenario. Indeed, the average density of our network is .20 and since this is well below .5 and quite stable over time we would expect a negative parameter for the *density* effect.

[17] We use *italic* letters referring to effects to avoid misunderstandings, since some terms correspond to common network measures.

[18] This does not affect the calculation since all x_{ii} are zero anyway.

[19] In the very long run the density, defined as the fraction of established links out of all possible links of the network would in the absence of countervailing effects tend to 1.

The second effect is the *reciprocity* effect which is defined as:

$$s_{i2} = \sum_{j=1}^{n} x_{ij} x_{ji}, \tag{10}$$

i.e. the number of banks to which i has at the same time a borrowing and a lending relation. A positive parameter of this effect would indicate that banks c.p. are more likely to lend money to another bank if it had already borrowed money from this bank in the same quarter and vice versa. In order to investigate the importance of lasting reciprocal relations, we introduce another related effect called *reciprocity persistence*. This allows us to assess whether banks value already existing mutual credit relations differently from newly created one. This effect is covered by:

$$s_{i3} = \sum_{j=1} x_{ij}^{b} x_{ji}, \tag{11}$$

where the only difference is the inclusion of x_{ij}^{b} instead of x_{ij}, which denotes the prevalent state in the previous quarter. Therefore, only if there has existed a link $x_{ij}^{b} = 1$ at time t_{m-1} could this effect become non zero. A positive (negative) parameter for this effect would indicate that banks are reluctant (positively inclined) to break up a mutual relation. Note that this effect evaluates the persistence of mutual links while the previous *reciprocity* effect indicates whether there is in general preference towards mutual relationships. The intuition is that established mutual relations should be worth more due to investment already undertaken in the past which holds true for human relations.[20] However, this reasoning is not as obvious for interbank relations, since credit relations already constitute a mutual contract. The average level of reciprocity, defined as the fraction of reciprocated relations among all established relations, is 20 percent (cf. Table 1) indicating that reciprocity in credit relations might be of minor importance.

The *transitive triplets* effect and the *3-cycles* effect investigate different aspects of transitivity, with transitivity referring to the influence of indirect relations. The *transitive triplets* effect for i is defined as[21]

$$s_{i4} = \sum_{j,k=1}^{n} x_{ij} x_{jk} x_{ik}, \tag{12}$$

[20] See e.g. Schaefer *et al.* (2010) and Agneessens and Wittek (2012).

[21] In the following it is understood that $i \neq j \neq k$ holds.

or the number of triadic relations in which i has a lending relation to j and k and additionally bank j has a lending relation to k. The corresponding parameter indicates, whether the indirect relation between j and k influences the probability of a lending relation to be formed from i to k or j. The *3-cycles* effect is defined by the sum of paths of length three completing a cycle between banks (i,j,k)[22]

$$s_{i5} = \sum_{j,k=1}^{n} x_{ij} x_{jk} x_{ki}, \qquad (13)$$

i.e. the number of triadic relations for bank i in which the flow of money completes a circle of length 3. It measures whether the two intermediate relations $x_{jk} = 1$ and $x_{ki} = 1$ make the link between i and j more likely. Note that the *transitive triplets* effect is in line with a locally hierarchical structure, while the *3-cycles* effect captures more of an extended reciprocity with a tendency towards emergence of clusters of mutual lenders and borrowers and, hence, is not in line with local hierarchy. The two triadic structures as shown in Figure 1 can be used to calculate two types of directed clustering coefficients.[23] The statistics CC^1 in Table 1 with an average of 58 percent of all possible triplets corresponds to the *transitive triplets* effect and CC^2 with an average of 15 percent to the *3-cycles* effect. These values in relation to the density indicate that links organized in a triadic structure as in the *transitive triplets* effect appear 2.74 more often than a random link, while links completing a cycle are 27% less likely to be formed. It is this heterogeneity in the occurrence of different types of triplets in the data that motivates us to include the pertinent effects in our model.

The final two structural effects implemented in the model are capturing the influence of the in- and outdegrees of agents. The *indegree-popularity* effect is defined as the sum of the square roots of the indegrees from the banks to which bank i has an outgoing link or the square root of the sum of the borrowing relations of those banks to whom bank i has a lending relationship:

$$s_{i6} = \sum_{j=1}^{N} x_{ij} \sqrt{\sum_{h=1}^{n} x_{hj}}. \qquad (14)$$

[22]A connection along (directed) links between two nodes i and j is called a path and the length of the path is the number of links crossed.

[23]For the calculations see Finger *et al.* (2013).

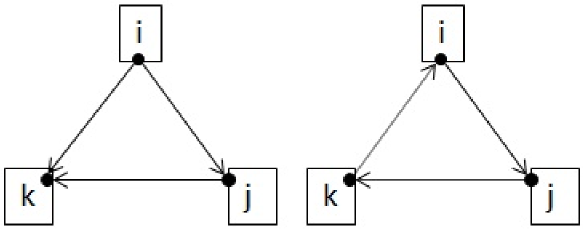

Figure 1: The left triadic structure corresponds to the *transitive triplets* effect CC^1. The right triadic structure illustrates the *3-cycles* effect CC^2 and is non-hierarchical, since all nodes have the same roles as lenders and borrowers.

It investigates whether banks with many borrowers are more 'popular' and tend to be accepted more easily as borrowers by other banks, where the square root takes capacity constraints into account.[24] This will lead to or sustain a certain heterogeneity of the indegrees and would make high degree nodes persistent over time. Therefore, it would also indicate hierarchy at the global level. The *outdegree-activity* effect is defined as the sum of the outdegree of bank i times the square root of this sum or the square root of lending relations of bank i times the lending relations of bank i

$$s_{i7} = \sum_{j=1}^{N} x_{ij} \sqrt{\sum_{j=1}^{n} x_{ij}}, \tag{15}$$

where the square root again takes capacity constraints into account.[25] The effect measures if their is a cumulative effect of 'active' banks with already many lending relations tending to be more eager to form additional connections. Analogous to the *indegree-popularity* effect a positive parameter would exert an influence towards a high dispersion among the outdegrees and persistence of their distribution.

The dyadic covariates are the the square root of trades (*past trades*) and the average rate (*past rates*) each for the last year. In both cases only the so-called main effect is implemented, which is defined as the sum of $i's$

[24]We could also design this effect as a linear one. However, the linear *indegree-popularity* effect is most of the time insignificant if both effects are implemented.

[25]The linear effect without the square root is again left out, because it is most of the time insignificant if both effects are implemented.

outdegree weighted with the corresponding value for the dyadic covariate. The past trades effect is

$$s_{i8} = \sum_{j=1}^{N} x_{ij} w_{ij}^{1}. \tag{16}$$

It measures whether lending relations are more likely if banks had already often exchanged liquidity in this direction during the last year. Note that the centering ensures (for all covariates) that a positive parameter indicates at the same time banks favouring regularly (above average) used relations and avoiding sparsely (below average) used ones. The *past rates* effect

$$s_{i9} = \sum_{j=1}^{N} x_{ij} w_{ij}^{2}, \tag{17}$$

measures the influence of interest rates between each ordered pair of banks of the last quarter, with w_{ij}^2 as defined in eq. (2).

The actor covariates are the size of the banks (as categorical variable as introduced above), whether the bank was assigned to the core or not according to Fricke and Lux (2014), the standardized lending rate and the standardized borrowing rate. For each of these actor covariates the same three effects are implemented in the model. The *size popularity* (or alter) effect is defined as the sum of $i's$ outgoing links weighted with the size v_j^1 of bank j,

$$s_{i10} = \sum_{j=1}^{N} x_{ij} v_{j}^{1}. \tag{18}$$

A positive parameter for this effect indicates that banks prefer lending relations to large banks which themselves would have more borrowing relations or a higher indegree and were therefore more 'popular'. Due to the centering a positive parameter indicates that banks prefer lending to banks which are above the average in terms of size. Hence, at the same time a positive parameter indicates that smaller than average banks are less attractive borrowers. Without the centering such a distinction would not be possible and a positive parameter would imply that all banks would be (to different degrees) more attractive.[26] The *size activity* (or ego) effect is the sum of $i's$

[26] The interpretation would not be affected, since larger banks are in both cases more attractive. However, the logic that all banks independently of their actual size are more attractive because of their size is problematic and other effects (mainly *density*) would have to be adjusted for this.

outdegree times its own size v_i^1

$$s_{i11} = \sum_{j=1}^{N} v_i^1 x_{ij} \tag{19}$$

and measures if the size of banks has an influence on their 'activity', i.e. the number of lending relations. The *size similarity* effect is defined as the sum of $i's$ outdegree each weighted with a similarity score

$$s_{i12} = \sum_{j=1}^{n} x_{ij} sim(v_i^1, v_j^1), \tag{20}$$

where $sim(v_i, v_j) = 1 - \frac{|v_i - v_j|}{R_v}$ and $R_v = max|v_i - v_j|$. Thus, the similarity is calculated as 1 minus the absolute dissimilarity of the pair (i,j) with respect to the range R_v of the normalized covariate and is therefore restricted to the range $[0, 1]$. A positive parameter for this effect indicates that banks with a similar size prefer to have relations with each other. The intuition would suggest that larger banks have more lending as well as borrowing relations and so we expect to find a positive parameter for the first two effects. The *size similarity* effect could be motivated by banks of the same size class being hit by similar or dissimilar liquidity shocks which would lead to preferences for connecting to banks of a similar size or of a different size category. For the core we also implemented the *core popularity*, *core activity* and *core similarity* effects

$$s_{i13} = \sum_{j=1}^{N} x_{ij} v_j^2 \tag{21}$$

$$s_{i14} = \sum_{j=1}^{N} v_i^2 x_{ij} \tag{22}$$

$$s_{i15} = \sum_{j=1}^{n} x_{ij} sim(v_i^2, v_j^2). \tag{23}$$

As with the size we would expect core banks to have more lending and borrowing relations and therefore positive parameters for s_{i12} and s_{i13}. In the case of the *core similarity* effect two countervailing forces could be at work. On the one hand, core banks are expected mostly to trade with each other, while peripherical banks are supposed not to. The larger number of peripherical banks might lead to a negative result.

Also for the lending rate the *lending rate popularity*, *lending rate activity* and *lending rate similarity* (with lending rates normalised as volume weighted deviations from the average a defined in sec. 2)

$$s_{i16} = \sum_{j=1}^{N} x_{ij} v_j^3 \tag{24}$$

$$s_{i17} = \sum_{j=1}^{N} v_i^3 x_{ij} \tag{25}$$

$$s_{i18} = \sum_{j=1}^{n} x_{ij} sim(v_i^3, v_j^3) \tag{26}$$

are considered as effects in the EVF. The intuition for these covariates could be that banks acting as market makers in the interbank market are able to charge their customers for this service and since market makers should be large intermediaries we expect again positive coefficients for the *popularity* and *activity* effects. If we adapt the same reasoning for the *lending rate similarity* effect we might expect a negative coefficient, since the market maker able to charge a high lending rate should trade with smaller banks rather than with other market makers.

The last actor covariate is the borrowing rate and again the same three effects

$$s_{i19} = \sum_{j=1}^{N} x_{ij} v_j^4 \tag{27}$$

$$s_{i20} = \sum_{j=1}^{N} v_i^4 x_{ij} \tag{28}$$

$$s_{i21} = \sum_{j=1}^{n} x_{ij} sim(v_i^4, v_j^4) \tag{29}$$

are included in our analysis. The most interesting effect should be the *borrowing rate popularity*, since a high borrowing rate should indicate a higher likelihood of default and, hence, higher counterparty risk would be associated with granting liquidity to this bank. Therefore, we expect a negative coefficient (β_{18}) for this effect, especially for the time after the start of the GFC. Not so obvious is what implication a high borrowing rate should have on the lending activity of banks. In case of the *borrowing rate similarity* one could argue similarly to the *lending rate similarity* effect that some kind of hierarchical ordering makes it more likely that more dissimilar banks are trading with each other.

3.3. Model Estimation

The huge number of possible network states ($2^{N(N-1)}$) makes an analytical solution of probabilities and expected values impossible, but Snijders (1996, 2001) introduced a method of simulated moments (MoM) approach to overcome this problem. Additionally, Snijders *et al.* (2010a) implemented a Maximum Likelihood approach (ML) and Koskinen and Snijders (2007) a Bayesian method. The reason for sticking to the MoM is twofold. First, simulation studies in Snijders *et al.* (2010a) have shown that the higher efficiency of the ML method is only relevant for small data sets, whereas ours can be considered as large in terms of the numbers of actors and the numbers of the changing relations in between two observations (distance) in comparison to previous applications. Second, the likelihood and Bayesian estimation methods require much more computing time which is particularly relevant for large networks like ours.[27] The remaining part of this section will briefly introduce the MoM approach.

The general idea is that sample moments (statistics) are the natural estimators of population moments (expected values of statistics). Since the test of Lospinoso *et. al* (2011) detects time heterogeneity in our application we estimate the model in a first step separately for each period and so we will obtain estimates of the period-specific set of parameters $\theta_m(\rho_m, \alpha_m, \beta_m)$ with a total number of parameters $L = 1 + E + K$. The parameters are estimated by equating the sample statistics z and the expected values of Z.[28] Hence, it is necessary to choose L statistics to solve the L-dimensional moment equation

$$\mathbb{E}_\theta Z = z. \tag{30}$$

The statistics Z have to be chosen such that the expected value $\mathbb{E}_\theta Z$ is sensitive to the parameter vector θ_m. The first quarterly network is only

[27] Snijders *et al.* (2010a) report a computational time for the ML approach for a smaller data set with much less effects that is about 17 times longer than for the MoM approach.

[28] Capital letters refer to the expected statistics Z and networks X constructed for simulations of the model, whereas z and x indicate observed statistics and networks.

used to condition on and, hence, no parameter estimates are obtained for this observation. Note that our empirical data will not be assumed to be observed in a stationary state or equilibrium of the actor-based choice process. As a consequence, we condition on the previous observation allowing for transient adjustment prior to convergence to a stationary distribution. Hence, each observation $t_m (m \leq M-1)$ is used as a conditioning event for the distribution of $x(t_{m+1})$ and so the simulated network is reset after each period to the observed network. This makes the estimation per period and the implementation of time dummies for all periods and effects equivalent. Following this, the moment equation for period t_{m+1} can be written as

$$\mathbb{E}_\theta\{Z(X(t_m), X(t_{m+1}))|X(t_m) = x(t_m)\} = z(x(t_m), x(t_{m+1})). \tag{31}$$

A sensitive statistic for the rate of change ρ_m which determines the expected 'amount of change' is

$$C = \sum_{i,j}^{N} |X_{ij}(t_{m+1}) - X_{ij}(t_m)|, \tag{32}$$

the 'observed total number of changes'. For the structural characteristics additionally included in the RF an appropriate statistic is

$$C_e = \sum_{i,j}^{N} s^e_{im}|X_{ij}(t_{m+1}) - X_{ij}(t_m)|, \tag{33}$$

where the 'observed total amount of change' is weighted with s^e_{im} and, hence, a positive parameter estimate α_e in Eq. (3) indicates that banks with a higher value of s^e_{im} are more active.

For the parameter β_k in the EVF a higher value of β_k means that all actors try to target a higher value of s_{ik}. An adequate statistic is

$$S_k = \sum_{i=1}^{N} s_{ik}(X(t_{m+1})), \tag{34}$$

because it is summing up the effect over all actors for the second observation period $(m+1)$. The statistic for the *reciprocity* effect for example counts the number of reciprocal ties at time $m+1$. At the beginning of each simulation of the network, the structural statistics and the covariates are assigned their values obtained in t_m, while during the simulation the network and the structural statistics may change while the covariates are fixed. For instance the first altered credit relation affects many structural statistics like out- and indegree and, thus, the next actor drawn by the RF faces a slightly different discrete choice problem. Note that in case of the *reciprocity persistence* effect x_{ij}^b remains fixed and so only the surviving links are counted in this statistic. For instance, a positive value for the *reciprocity persistence* effect would yield more mutual links in general, but would achieve this by a higher number of surviving links and not through the number of new mutual links created during this period.

For the numerical solution of the moment equations a version of the iterative Robbins-Monro algorithm (Robbins and Monro, 1951) is applied. After each run (r) the new parameter vector $\hat{\theta}_{r+1}$ is obtained from the old values $\hat{\theta}_r$ and the difference between simulated and observed statistics. One such step is defined by

$$\hat{\theta}_{r+1} = \hat{\theta}_r - a_\tau D^{-1}(Z_r - z), \tag{35}$$

where Z_r is the simulated value with parameters $\hat{\theta}_r$ for run r and $a_\tau D^{-1}$ determines the speed of adjustment of the parameter vector θ. The coefficient a_τ is decreased towards zero over the estimation process and defines the general speed of the adjustments. D is the estimate of the diagonal matrix $\frac{\partial}{\partial\theta}\mathbb{E}_\theta Z$ measuring how much $\mathbb{E}_\theta Z$ is changing with respect to the specific parameters in θ_r. Hence, after each run the parameters are changed depending on the discrepancy $(Z_r - z)$ between the simulated Z_r and observed statistic z.[29]

The complete estimation procedure consists of three phases. The first phase contains a small number of 50 runs to get a 'rough estimate' of $\frac{\partial}{\partial\theta}\mathbb{E}_\theta Z$ to define D. In this phase θ is fixed at pre-specified values. The starting values for the very first simulation are set equal to zero for all parameters except for the basic rate parameter ρ_m.[30]

In the second phase the Robbins-Monro algorithm is applied to estimate θ using D. It consists of 4 subphases, where $a_\tau = \{.4, .2, .1, .05\}$ remains constant during subphases and decreases between subphases.[31] At the start of a new subphase the average parameter values of the last subphase are

[29]The covariance matrix is approximated as in Schweinberger and Snijders (2007) by applying the delta method and the implicit function theorem.

[30]ρ_m is set equal to the total change in between t_m and t_{m+1}, because it is necessary to have a positive rate function to initiate a simulation.

[31]The end of each subphase is reached when the quasi autocorrelations $(Z_r - z) *$

used as the starting point ($\hat{\theta}_r$) in the Robbins-Monro algorithm (Eq. 35). Accordingly, the final estimate ($\hat{\theta}$) is the average of the parameter values obtained during the 4th subphase. In the third and final phase θ is kept constant at the estimated values for 5000 runs. The results of this phase are used to calculate standard errors and check the convergence of the algorithm.[32]

4. Estimation Results

4.1. Full Sample Estimation

In our application all effects introduced above are implemented.[33] The period investigated extends from the first quarter of 2002 until the end of 2010.[34]Since, the test of Lospinoso *et. al* (2011) points to time heterogeneity for almost all effects and periods we estimate the model per period rather than introducing time dummies, while both procedures should yield the same results. The t-statistics for convergence are always below .1 for all effects and indicate excellent convergence of the algorithm according to Snijders *et al.* (2010b).[35]

To analyze the common significance of each effect for the whole sample, we apply the two-step multilevel analysis proposed by Snijders and Baerveldt (2003). First, a preliminary mean is estimated by taking the average of the 36 estimates. This preliminary estimate is unbiased but not efficient and its statistical error stems from two sources: the variance in every period for which we have an estimate (the variance of each parameter estimate itself) and the variance across the periods. Next, we use the

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($Z_{r-1} - z$) of two subsequent runs become negative for all statistics. This means that the adjustment direction for every parameter has been changing for the last two updates of θ and so one can assume that the trajectory had reached a limit point.

[32]If the convergence turns out to be not sufficient another run of the Robbins-Monro algorithm is initiated. In this new run, phase 1 is skipped and instead the estimated parameter values of the previous run are used to restart the estimation procedure with phase 2.

[33]All calculations in this paper are done using R (cf. R Development Core Team, 2012). For estimating the SAOM the routines of Ripley *et. al* (2013) were applied.

[34]The transactions of the year 2001 are used to calculate the first set of dyadic covariates (*past trades*, *past rates*) and the network of the 4th quarter 2001 is used for initialization.

[35]They are calculated as average standardised deviations of the simulated and observed statistics of the MoM approach over the 5000 runs in phase 3, i.e. dividing the mean differences by the standard deviation over all simulations.

known variance of the single estimates to get an unbiased estimator for the variance across periods. Now we can determine the statistical error for each period separately and we use this in a weighted least squares regression in which the weights depend negatively on the variance of the single estimates. The results for the complete sample are summarized in Table 3.[36] The first column states the effect and the second to which category it belongs. The third to fifth column display the estimates for the mean parameter, its standard error and the corresponding p value. The last column shows for how many estimation periods the effect was different from zero at a 5% significance level, where the first term in brackets indicates positive significance, the second negative significance and the third lack of significance.[37]

Interpreting the results it is necessary to keep in mind the differences between interbank credit relations and human relationships. For instance, all credit relations are mutual contracts, yet we define the flow of money and the corresponding risk taken by the lending bank as the direction of the link.

The rate is 36.055 on average and is necessarily positive, since two subsequent networks are always different. Figure 2 shows that the estimated rate of activation and the number of banks both decrease during the sample period and are highly correlated (with a correlation coefficient of .689). However, the rate tends to be much more volatile and we especially observe outbursts of activity before and at the beginning of the GFC, which could be seen as indicators for a 'nervous' market environment. The rate parameter drops sharply after the last and most pronounced spike at the beginning of the GFC and assumes its lowest values over the whole time horizon during the continuation of the GFC in 2009/10 which very likely is the consequence of overall reduced activity in the interbank market and a stronger concentration on well-established links.The *size* effect implemented in the RF has an estimated mean of .1566 and is significant at the 1% level. For instance, a bank of size category 5 acts on average about 2 times as

[36]As mentioned above, the model has been estimated in each period by considering only those banks active in t_m and t_{m+1}. Market entry and exit are, therefore, neglected as they will certainly be driven by forces outside of our present framework, i.e. mergers and acquisitions. We estimated the model also in different specifications, where e.g. banks were allowed to enter and leave the market, but got always very similar results.

[37]The results are in general qualitatively the same for significance levels of 1% and 10% and all results referred to but not explicitly shown are available from the corresponding author upon request.

effect	category	mean	s.e.	p-value	significance
rate		36.055			
size	rate	.1566	(.00084)	.001***	[32|-|4]
density (outdegree)	structural	-4.2010	(.0647)	.001***	[-|36|-]
reciprocity	structural	.6797	(.0508)	.001***	[23|-|13]
reciprocity persistence	structural	-.7371	(.0957)	.001***	[-|8|28]
transitive triplets	structural	-.0029	(.0010)	.006***	[-|9|27]
3-cycles	structural	-.0236	(.0026)	.001***	[-|34|2]
indegree pop. (sqrt)	structural	.3580	(.0061)	.001***	[36|-|-]
outdegree act. (sqrt)	structural	.2157	(.0056)	.001***	[36|-|-]
past trades	dyadic cov.	.1946	(.0086)	.001***	[36|-|-]
past rates	dyadic cov.	.4087	(.3959)	.309	[9|7|20]
size popularity	actor cov.	.0065	(.0078)	.410	[8|6|22]
size activity	actor cov.	-.0437	(.0115)	.001***	[4|21|11]
size similarity	actor cov.	.0536	(.0170)	.003***	[6|-|30]
core popularity	actor cov.	.2174	(.0239)	.001***	[27|-|9]
core activity	actor cov.	.2497	(.0315)	.001***	[27|1|8]
core similarity	actor cov.	-.0062	(.0129)	.632	[3|6|27]
lending rate pop.	actor cov.	-.0478	(.0754)	.530	[2|4|30]
lending rate act.	actor cov.	-.2855	(.1831)	.128	[5|9|22]
lending rate sim.	actor cov.	-.1581	(.0618)	.015**	[3|11|22]
borrowing rate pop.	actor cov.	-.3885	(.2820)	.177	[8|13|15]
borrowing rate act.	actor cov.	.0991	(.1179)	.407	[5|3|28]
borrowing rate sim.	actor cov.	-.1146	(.0547)	.044**	[3|7|26]

Table 3: The estimation results for the 36 quarters from 2002 until 2010. The columns state the name of the effect, the category it belongs to, the estimated mean, its standard error and p-value from the two-step weighted least squares approach following Snijders and Baerveldt (2003) and in how many periods the estimated parameters were significant on the 5% level [positive significance|negative significance|lack of significance].

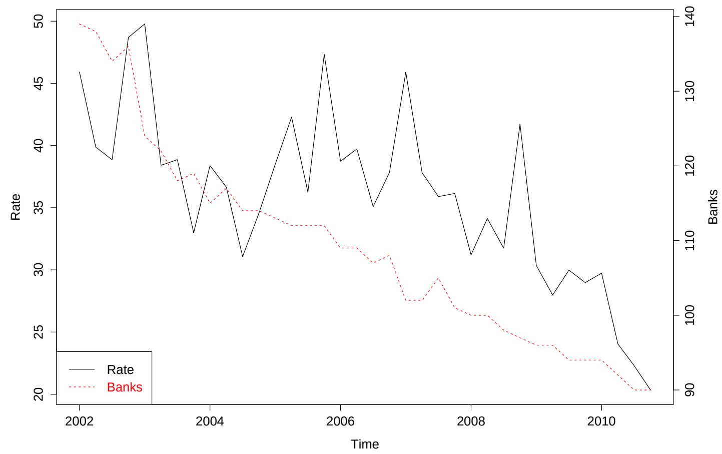

Figure 2: The evolution of the basic rate parameter and the number of banks (dashed) from 2002Q1 to 2010Q4.

often as a bank of size= 1.[38] Note that the RF covers activity both in creation and termination of links. The spike at the beginning of the GFC was accompanied by a strong decline in the density (Fricke and Lux (2014)), however, a high rate could also come along with an increasing or stable density. Hence, this effect allows by itself no prediction of the development of such network statistics like the density.

Now we turn to the OF, which as stated above determines why banks establish or dissolve outgoing links. The *density* effect is always negatively significant with a mean of -4.201 indicating capacity constraints in the accumulation of links. Note, however, that many other effects do also include the outdegree of actor i, so that the coefficient alone does not explain completely the evolution of the density.[39]

Since both the *reciprocity* effect and the *reciprocity persistence* effect are implemented we can distinguish between the tendencies for creation and deletion of mutual links. The coefficients are .680 for the *reciprocity* effect and $-.737$ for the *reciprocity persistence* effect, and both effects are

[38]To calculate this it is necessary to insert the centered covariate values in Eq. (8). The effect was four times insignificant.

[39]It acts similar to an intercept in a regression framework.

significant at the 1% level.[40] This shows that banks prefer to create mutual relations, i.e. already borrowing money from a bank makes it more likely to also lend money to it. On the other hand banks value maintaining such mutual relations less than creating them and on balance, i.e. summing up both effects ($.6797+(-.7371) = -.0574$), they appear practically indifferent between dissolving a mutual or a non-mutual relation.[41] The negative result for the *reciprocity persistence* effect stands in stark contrast to all former applications of the SAOM. The reason is that humans highly value mutual relations and even more those in which they already 'invested' effort and time.[42] However, in case of the interbank market relations predominantly go in one direction with the extreme case of (mainly) small banks using the market almost exclusively to lend or borrow. Hence, the intuition for this results should be that often strong one-sided relations exist, which are relatively seldomly reciprocated. To give an example, bank i might be borrowing money from bank j ($x_{ji} = 1$) on a regular basis. Because of this relation it becomes more likely that, if bank i has an excess of liquidity bank j will again be the counterparty ($x_{ij} = 1$). In the next period x_{ij} is likely to be zero again, since bank i might not lend money at all. This behaviour leads to the finding that banks have a certain preference for mutual relations, but are not inclined to purposefully maintain them over time.

The *transitive triplets* effect ($-.0029$) and the *3-cycles* effect ($-.0197$) are both negatively significant at the 1% level. Note that interpreting the 'strength' of these effects one has to keep in mind that, in contrast to e.g. *reciprocity*, a link can close several triadic structures at once. The negativity of the *3-cycles* effect indicates local hierarchy and is in line with the corresponding low directed clustering coefficient CC^2. On the other hand the high value for the other directed clustering coefficient CC^1 stands in contrast to the significantly negative coefficient for this configuration in the evaluation function. It, thus, appears that the high empirical value of CC^1 is not generated consciously by the agents, but apparently emerges out of

[40]The single effects per period are 13 and 28 times not significant, but Fisher's combination of one-sided p-values indicates that it can be excluded that the parameters have the opposite sign of their estimated means.

[41]If we introduce only the *reciprocity* effect without distinguishing between formation and abortion of a mutual link it is insignificant for almost all specifications tested. This observation supports our interpretation in the main text.

[42]Schaefer *et al.* (2010) and Agneessens and Wittek (2012) included solely the *reciprocity* effect, whereas Snijders *et al.* (2010b) implemented the *reciprocity persistence* effect as well.

the interplay of other effects.[43] Hence, indirect links do not work by themselves as an incentive for banks to form a directed link, which supports the idea that banks are mainly interested in their direct counterparty. This is again in contrast to human relations, where the *transitive triplets* effect is often found to be positive, while the results concerning the *3-cycles* effect are mixed suggesting that some groups are hierarchically ordered but others are not.[44]

The last two entirely structural effects are the *indegree popularity* effect and the *outdegree activity* effect. Both are positively significant at the 1% level with respective coefficients of .358 and .216.[45] Hence, there appear positive feedback effects to be working in both cases. As a consequence both degree distributions should display persistent dispersion in the sense that banks with many (few) lending or borrowing relations are likely to have many (few) in the future as well. Moreover, this provides evidence for an enduring hierarchical structure with respect to degrees, while it does not indicate that banks with a high indegree would also automatically have a high outdegree.[46]

After considering the structural effects we turn to the covariate related effects. The square root of trades in the last year is a dyadic covariate and thus specific for each ordered pair (i,j). The corresponding *past trades* effect is positively significant with a mean of .194 and shows that banks prefer enduring lending relations. Hence, trading history is strongly affecting the likelihood of future trades even in an electronic broker market such as the e-MID.[47] The *past rates* effect on the other hand is insignificant. Hence, a specifically low or high rate realized for the ordered pair (i,j) in the past is not systematically affecting the decisions of bank i with respect to lending

[43] Estimating a very simple model with just *density*, *reciprocity*, *transitive triplets* and *3-cycles* we get higher values and always significant results in the expected direction to the corresponding clustering coefficients for both triadic effects.

[44] See for a positive *transitive triplets* effect but negative *3-cycles* effect in human relations Cheadle and Schwadel (2012) and Agneessens and Wittek (2012), whereas Lazega *et al.* (2012) found both effects to be positive.

[45] This is often found for human relations as well. See e.g. Lazega *et al.* (2012).

[46] The correlation between both degree distributions is on average only .12 and for some periods even negative.

[47] To get an understanding of how strong this effect actually is we have to consider that the covariate assumes values up to 17.52. We alternatively considered other covariates to measure the strength of past relations, e.g. following Affinito (2012) the duration, and got very similar results.

money to bank j in the future.[48]

The parameter values of the actor covariate effects for the single periods often change their sign and except for the size *similarity* effect and the core *popularity* effect are even positively and negatively significant at different points in time. Applying a Wald test to the three covariate related effects combined indicates that they are often significant. To be precise, the according test statistics shows 27 times for the size, 36 times for the core, 19 times for the lending rate and 25 times for the borrowing rate significance at the 5% level. There is no clear pattern visible for the significance for any specific time period or interplay among different effects.

The size and core covariates might measure similar attributes of the banks, since it could be argued that mostly large banks might belong to the core. The results, however, disagree to some extent with this intuition. The respective estimated coefficients are .007 for the *size popularity* effect and $-.044$ for the *size activity* effect and only the latter is significant at the 1% level. So larger banks are surprisingly not more popular and even less active. The *similarity* effect (.054) is positively significant and shows that banks of a more similar size are more likely to trade with each other. Core banks on the other hand are more popular (.142) and more active (.293) and both estimates are significant at the 1% level. The significance of these effects, keeping in mind that we additionally control for e.g. *indegree popularity* and *outdegree activity* which also detect hierarchical structures, shows that the core-periphery model is able to retrieve additional information in detecting intermediaries beyond a mere categorisation of the size. The *core similarity* effect ($-.006$) is insignificant, which should be due to its two opposing forces namely that core banks are supposed to trade with each other, while the opposite should hold for the peripherical banks.

All interest rate related effects for the single periods are often insignificant and repeatedly switch their sign. Both *similarity* effects are negatively significant at the 5% level. This indicates that banks prefer to trade with banks with a different profile, which again could be interpreted as some kind of hierarchical ordering in the interbank market. Note that during a transaction the rate is obviously the same for both counterparties, yet for one it is the borrowing rate and for the other the lending rate and the low correlation ($-.075$) between the two average interest rates across banks indicates that a high lending rate reveals almost no information about the borrowing rate and vice versa. The other results are surprising, since no other effect is

[48]The effect is 7 times negatively and 9 times positively significant per period.

significant and so both interest rates seem not to systematically affect the popularity or activity of a bank. For instance, a higher borrowing rate that arguably should indicate a higher likelihood of default does not influence other banks directly in their decisions of lending money to this bank.[49] In total only 2 out of 6 effects related to interest rate actor covariate are significant and some of the results are counter-intuitive. However, this might be expected for the tranquil period until the GFC, where the interest rates were overall very similar.

4.2. Before and After the Financial Crisis

In order to see whether the structure of the interbank market experienced significant changes with the onset of the financial crisis we split the sample into two parts. Again, the two-step weighted least squares approach from Snijders and Baerveldt (2003) is used to estimate the model for 26 periods from the first quarter 2002 until the second quarter 2008 and the remaining 10 periods from the 2nd quarter of 2008 until the 4th quarter of 2010. While it might be somewhat hard to say when the GFC exactly started, we believe that letting the second sample begin with the default of Lehman Brothers constitutes the most plausible way of splitting up the data into a pre-crisis and crisis period.

The results in Table 4 for the pre-crisis period show that the overall results differ only in very few aspects from the results for the complete sample, which might have been expected since it is the longer and more tranquil period. Thus, we will briefly address the only change before we are going to compare the two subperiods with each other.[50] The *lending rate activity* effect ($-.462$) is now becoming significant at the 10% level and so in the tranquil period we see the expected economic relationship of a lower lending rate leading to a higher number of borrowers (i.e. higher demand for credit).

The next step is to compare these results to the ones in Table 5 for the time after the onset of GFC. Again, many results are very similar to the pre-crisis period.[51] One major difference is that post-Lehman, all interest rate related effects have become insignificant. In Table 6 we investigate whether

[49] It is 8 times even positive significant indicating high variation.

[50] Additionally, *transitive triplets* and the *lending rate similarity* effect are now only significant at the 10% level (complete sample: 1% and 5%, respectively) .

[51] Note that the *transitive triplets* effect is now significant at the 1% level (pre-crisis 10%).

effect	category	mean	s.e.	p-value	significance
rate		38.879			
size	rate	.1613	(.0078)	.001***	[25|-|1]
density (outdegree)	structural	-4.2733	(.0610)	.001***	[-|26|-]
reciprocity	structural	.7124	(.0558)	.001***	[20|-|6]
reciprocity persistence	structural	-.8384	(.0960)	.001***	[-|7|19]
transitive triplets	structural	-.0018	(.0010)	.081*	[-|6|20]
3-cycles	structural	-.0175	(.0011)	.001***	[-|25|1]
indegree pop. (sqrt)	structural	.3535	(.0068)	.001***	[26|-|-]
outdegree act. (sqrt)	structural	.2125	(.0065)	.001***	[26|-|-]
past trades	dyadic cov.	.2025	(.0083)	.001***	[26|-|-]
past rates	dyadic cov.	.671	(.5393)	.225	[9|5|12]
size popularity	actor cov.	.0000	(.0100)	.998	[6|6|14]
size activity	actor cov.	-.0595	(.0114)	.001***	[1|17|8]
size similarity	actor cov.	.0474	(.0152)	.004***	[4|-|22]
core popularity	actor cov.	.1890	(.0289)	.001***	[18|-|8]
core activity	actor cov.	.2175	(.0359)	.001***	[18|1|7]
core similarity	actor cov.	-.0210	(.0146)	.164	[2|6|18]
lending rate pop.	actor cov.	-.0210	(.0776)	.789	[1|2|23]
lending rate act.	actor cov.	-.4620	(.2389)	.065*	[3|6|17]
lending rate sim.	actor cov.	-.1670	(.0826)	.054*	[3|9|14]
borrowing rate pop.	actor cov.	-.5774	(.3833)	.145	[7|10|9]
borrowing rate act.	actor cov.	-.0387	(.1196)	.749	[2|3|21]
borrowing rate sim.	actor cov.	-.1476	(.0604)	.022**	[1|5|20]

Table 4: The estimation results for the 26 quarters from the 1st quarter of 2002 until the 2nd quarter of 2008. The columns state the name of the effect, the category it belongs to, the estimated mean, its standard error and p-value from the two-step weighted least squares approach following Snijders and Baerveldt (2003) and in how many periods the estimated parameters were significant on the 5% level [positive significance|negative significance|lack of significance].

effect	category	mean	s.e.	p-value	significance
rate		28.713			
size	rate	.1421	(.0252)	.001***	[7|-|3]
density (outdegree)	structural	-4.0008	(.1197)	.001***	[-|10|-]
reciprocity	structural	.5508	(.1166)	.001***	[3|-|7]
reciprocity persistence	structural	-.3445	(.2346)	.176	[-|1|9]
transitive triplets	structural	-.0080	(.0023)	.007***	[-|3|7]
3-cycles	structural	-.0485	(.0062)	.001***	[-|9|1]
indegree pop. (sqrt)	structural	.3722	(.0130)	.001***	[10|-|-]
outdegree act. (sqrt)	structural	.2255	(.0112)	.001***	[10|-|-]
past trades	dyadic cov.	.1742	(.0219)	.001***	[10|-|-]
past rates	dyadic cov.	-.2728	(.3172)	.412	[-|2|8]
size popularity	actor cov.	.0232	(.0077)	.015**	[2|-|8]
size activity	actor cov.	-.0006	(.0255)	.982	[3|4|3]
size similarity	actor cov.	.0697	(.0532)	.223	[2|-|8]
core popularity	actor cov.	.3005	(.0291)	.001***	[9|-|1]
core activity	actor cov.	.3386	(.0584)	.001***	[9|-|1]
core similarity	actor cov.	.0453	(.0210)	.059*	[1|-|9]
lending rate pop.	actor cov.	-.2075	(.2002)	.327	[1|2|7]
lending rate act.	actor cov.	.1316	(.2329)	.586	[2|3|5]
lending rate sim.	actor cov.	-.1279	(.0878)	.179	[-|2|8]
borrowing rate pop.	actor cov.	.0501	(.2591)	.851	[1|3|6]
borrowing rate act.	actor cov.	.4481	(.2664)	.127	[3|-|7]
borrowing rate sim.	actor cov.	-.0196	(.1186)	.872	[2|2|6]

Table 5: The estimation results for the 10 quarters from the 2nd quarter of 2008 until the 4th quarter of 2010. The columns state the name of the effect, the category it belongs to, the estimated mean, its standard error and p-value from the two-step weighted least squares approach following Snijders and Baerveldt (2003) and in how many periods the estimated parameters were significant on the 5% level [positive significance|negative significance|lack of significance].

the coefficients in Table 4 and 5 are significantly different by applying a two sample t-test.[52] The *reciprocity persistence* effect is becoming insignificant and we also find that the difference of the pertinent parameter between the two subperiods (.4939) is significant at the 10% level.[53] Thus, taking both *reciprocity* effects together, banks seem not so indifferent anymore to giving up existing mutual relationships. However, interpreting this as a sign for overall favouring mutual relations more might be too far fetched, since the the level of reciprocity fell during the period. In case of the *core similarity* effect becoming positively significant at the 10% level one has to keep in mind that two opposing forces are measured here at the same time, since core banks should be attracted to each other while the opposite by definition holds for those classified as peripherical banks. Thus, this could either indicate that peripherical banks avoid each other less than before or that core banks are relying even more heavily on each other. The fact that some banks dropped out of the core[54] due to the GFC might indicate that these 'new' peripherical banks still relatively frequently trade with each other and drive this finding.[55]

More interesting is that the size seems to play a completely different role, since all three related effects change with the onset of the financial crisis. The *size activity* and *similarity* effect are becoming insignificant. Thus, larger banks are not less active and banks being more equal in terms of size are not more likely to trade with each other anymore. On the other hand the *size popularity* effect is positively significant for the second period, which indicates that banks prefer to transmit their excess liquidity to larger banks. Furthermore, the difference in the two estimates for *activity* and *popularity* is positively significant. This indicates that the attractivity of larger banks improved after the GFC and this might be due to the belief that the largest banks entail less counterparty risk. However, we are not able to determine to which extent (if any) this is driven by the believe that the government would have to rescue them, which would reduce their counterparty risk to literally zero. This is additionally supported by the

[52]The test statistic is $t = \frac{\theta_{PRE} - \theta_{GFC}}{\sqrt{se^2_{PRE} se^2_{GFC}}}$, where the subscripts PRE and GFC refer to the period before and after the start of the financial crisis.

[53]The level of reciprocity drops in the quarter after the Lehman collapse and Finger *et al.* (2013) detected a structural break in this descriptive variable.

[54]Before the crisis on average 28% of the banks belonged to the core, afterwards only 23%.

[55]See Fricke and Lux (2014) for the exact results.

effect	category	difference	p-value
size	rate	-.0191	.485
density (outdegree)	structural	.2725	.073*
reciprocity	structural	-.1616	.243
reciprocity persistence	structural	.4939	.083*
transitive triplets	structural	-.0062	.037**
3-cycles	structural	-.0309	.001***
indegree pop. (sqrt)	structural	.0187	.234
outdegree act. (sqrt)	structural	.0130	.341
past trades	dyadic cov.	-.0283	.258
past rates	dyadic cov.	-.9438	.166
size popularity	actor cov.	.0232	.100*
size activity	actor cov.	.0589	.064*
size similarity	actor cov.	.0223	.696
core popularity	actor cov.	.1115	.024**
core activity	actor cov.	.1211	.111
core similarity	actor cov.	.0663	.029**
lending rate pop.	actor cov.	-.1865	.408
lending rate act.	actor cov.	.6036	.116
lending rate sim.	actor cov.	-.0390	.753
borrowing rate pop.	actor cov.	.6275	.208
borrowing rate act.	actor cov.	.4868	.130
borrowing rate sim.	actor cov.	.1280	.361

Table 6: The results for the two sample t-test comparing the estimation results for the two subperiods before (in Table 4) and after (in Table 5) the GFC. The columns state the name of the effect, the category it belongs to, the difference between the two estimates and the pertinent p-value.

fact that the difference of the always significant *core popularity* effect is positively significant after the GFC, as well. Hence, larger and core banks have become even more attractive as borrowers which might be related to their seemingly lower default risk. The two triadic effects, *transitive triplets* and *3-cycles* are negatively significant in both subperiods. However, their significant differences indicate that banks avoid both kinds of intermediate relations even more after the crisis.

Finally, all three previously significant interest rate related effects are becoming insignificant. This is surprising since Raddant (2012) found that the spread widened after the GFC and so high borrowing rates should eventually indicate a higher likelihood of default and become an important signal. On the other hand, banks which have to pay high borrowing rates might be (more often) not able to acquire the desired liquidity from a single lender or avoid such deals on an electronic platform such as the e-MID and this could offset the aforementioned reasoning. Overall, interest rates seem to have no systematic impact on banks creating or ending their lending relations after the GFC. In any case, the results indicate that banks did not selectively restrict lending to counterparties with high borrowing rates. With the complete lack of significance of interest rate related effects in the crisis period, the contract rate does not appear to be an ex ante decisive causal criterion to enter a credit transaction which supports the relevance of established relations between lenders and borrowers after the onset of the financial crisis.

5. Concluding Remarks

We have investigated interbank lending relations documented in the e-MID electronic market via the actor-oriented model of network formation developed in sociology. Such an approach is motivated by previous statistical evidence for relationship lending (e.g. Cocco *et al.*, 2009) and provides the opportunity to study more directly the factors determining the formation (or dissolution) of lasting business relationships.

The most intriguing result is that the behaviour of the banks managing their lending relations was relatively robust throughout the complete sample period, which is supported by the very similar results for the periods before and after the GFC. Throughout every single period the finding that the past trades effect was significant highlights the importance of relationship banking. Hence, even on an electronic platform like e-MID where every bank has the opportunity to observe all the quotes and so the cost to enter into a contract with 'new' counterparties is very low banks heavily rely on well established business relations.

Rather surprising is the role of (average) interest rates on the behaviour of banks, because after the GFC there is no significant effect remaining and never did a high borrowing rate, indicating a higher default probability, make banks less attractive as counterparty for lending banks. However, the public character of the e-MID market may bias these results, since a bank would perhaps shy away from indicating publicly urgent liquidity needs by quoting a very high interest rate. So one might argue that in such a scenario the bank would rather try to get the liquidity via OTC markets not sharing this 'negative' information with all participating banks. Nevertheless, activating privately (over-the-counter) an established link would support the relevance of relationship banking. Additionally, banks associated with high (counterparty) risk could have more problems to acquire the desired level of liquidity from a single lender. On the other hand, the two most intriguing changes due to the GFC support that the perception of counterparty risk changed. First, larger banks became more popular and stopped being less active and core banks became even more popular and even more active. Here it could be reasoned that larger and core banks have a lower probability of default. However, we are not able to address the reason for this directly and so we can not distinguish whether these banks seem less risky due to their business performance and/or the believe that the government would have to step in in the case of their default to prevent a meltdown of the complete financial system. Second, banks avoid both kinds of intermediate relations more and by this reduce their *indirect* counterparty risk and the overall connectivity of the system (as it is reflected in a decreasing density).

An interesting aspect of the SAOM model is that we can scrutinize the interrelation between aggregate properties and individual behaviour. As concerns intermediate links both triadic effects never work as an incentive for banks to create a lending relation, but often have the contrary effect. This indicates that banks focus on their direct counterparty or try to avoid too much indirect counterparty risk. However, at the same time this means that the high directed clustering coefficient (CC^1) apparently emerges out of the interplay of other effects and seems to be an unintended feature of the overall network.

Another case where we observe unexpected behaviour is the *reciprocity* effect. Here the global statistic shows very similar values to the density (i.e.

a random number of reciprocal links) and so one would expect that banks do not care whether a relation is mutual or not. However, banks prefer to form mutual relations, while they seem to be indifferent to maintaining their relationships as a reciprocal one over time. The intuition is that relations are often predominantly pointing in one direction, but the existence of this stable relation makes it more likely that the familiar counterparties sometimes act in the opposite direction as well, creating a transient mutual relation. The strength of this one sidedness of many relations is remarkable, since we aggregate networks on a quarterly basis.

For the other bank specific features we see that larger banks become more popular borrowers after the beginning of the GFC. For core banks (as identified independently by Fricke and Lux, 2014, for the same sample) we find that they are both more popular and more active in the interbank market. Hence, the core-periphery model does not simply assign the biggest banks to the core, but includes important additional information in detecting intermediaries.

To sum up, we see that banks display persistent behavioral regularities over time, which should ensure (as it is the case) persistent structural features of banking network in terms of e.g. hierarchy and degree distributions, but also strong and lasting relations. These bonds seemingly helped the network to persist during the GFC. Moreover, the findings regarding, e.g. reciprocity and clustering, indicate that the SAOM model is a good start to understand the incentives and resulting behavior of banks managing their relations in the interbank market, and that an actor-based analysis provides important additional insights on top of purely statistical investigations of interbank lending relations. Revealed behavioral regularities could be integrated in models of bank behavior and could be used as behavioral assumptions in simulation models designed for stress-testing of the resilience of the interbank market.

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