Network formation in the Euro interbank market: A longitudinal analysis of the turmoil

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Abstract

This paper models the dynamics of counterparty selection in the network of transactions characterizing the Euro interbank market. We estimate Stochastic Actor-Oriented Models for network dynamics which detect the existence and direction of strategic behaviour. We use data on overnight contracts from the Euro Electronic Market for Interbank Deposits (e-Mid) during 2006-2009 to construct a network for each year. Our results indicate that banks build cooperative hierarchical networks that are characterized by 'local central banks', and by a specialization of roles. The turmoil has induced two main changes in the structure of e-Mid. First, relationship lending becomes all the more important in a phase of market turbulence. The propensity to act as a counterparty for a bank with which there are existing ties increases after August 2007. Second, the distinction of roles between lenders and borrowers weakens over the sample period.

Keywords: Market microstructure, interbank markets, turmoil, network analysis, stochastic actor-oriented models, time heterogeneity.
JEL classification: D85, G01, G10, G21.

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1 Introduction

The recent economic turmoil has shed light on the crucial role of the interbank market in the functioning of the world financial system. In this regard, the idea of 'too interconnected to fail' (see Haldane, 2009) has been proposed to study the risk of 'contagion' of shocks across financial institutions. The 'too interconnected to fail' approach underlines that the banking system can be conceived as s system of relationships, where banks are actors and money flows are ties (e.g., see Chan-Lau, Espinosa-Vega, Giesecke, and Sole, 2009). This has paved the way for the application of tools from social network analysis to economic and financial issues that are typically examined with traditional econometric methods.

Following this methodological perspective, we study the selection of counterparties and its relation to changes in network structure during the recent episode of financial market turmoil. We examine the persistence and enforcement of distortions in the lending behaviour of banks. Our empirical analysis is based on a newly-developed class of social-network frameworks known as Stochastic Actor-Oriented Models - SAOM henceforth. A SAOM is concerned with explaining why and how actors get engaged into complex network configurations (e.g., see Wasserman and Faust, 1994). The key aspect of this approach is that it models the persistence in network ties. In other words, we focus on 'states' rather than 'events' (e.g., see Snijders, 2001; Snijders, van de Bunt, and Steglich, 2010).

We estimate a SAOM on data for bilateral trades in the Electronic Market for Interbank Deposits - e-Mid - of the Euro area from January 2006 to December 2009. We concentrate on contracts with overnight maturity, since this is the most traded instrument in e-Mid. The sample period contemplates three phases of market evolution. It starts with a period of smooth functioning of the interbank market. The beginning of the turmoil in August 2007 is then followed by a shift into a global crisis in October 2008.

There are three main reasons for SAOM to represent a suitable modelling approach for the scope of our investigation. The first one is that e-Mid is a transparent market. This means that each actor enjoys complete information on the structure of exchanges in the whole network. Each bank is interested in maximizing its own profits, in the same way as actors in social relation applications of SAOM are interested in maximizing their utility. Finally, our aim is to explain changes in the structure of transactions occurring over time, rather than short-lived actions and reactions to exogenous shocks.

We find that trading in e-Mid is characterized by frequent changes to the network structure. The probability of observing changes to network ties increases largely after August 2007. In this sense, the turmoil period is associated to instability of relations in the interbank market place. Our results confirm the importance of forms of 'relationship lending' documented by Cocco, Gomes, and Martins (2009), among others. Banks have a low propensity to lend to institutions that are not already a counterparty. Moreover, they tend to build ties based on mutual support. For instance, lenders tend also to borrow from banks with which they are already trading. The exchanges are characterized by hierarchical ordering in each network.

We provide evidence for two main structural features of e-Mid. The first aspect is that there are key actors that control the supply of liquidity to the market (see also Liberati, Marzo, Zagaglia, and Zappa, 2012). The second property is related to the distinction of roles between borrowers and lenders. We find that the large lenders are less likely to act as borrowers. Moreover, there is a higher probability for ties to occur between banks with different lending propensities.

What is the impact of the turmoil on the network structure in e-Mid? The model estimates point to two statistically-significant types of effects. The propensity to establish mutual support between counterparties increases after August 2007. This is indicative of the increasing importance of relationship lending in a phase of market turbulance. On the other hand, the distinction of roles between lenders and borrowers weakens over the sample period.

This paper is organized as follows. Section 2 discusses the main structural features of the interbank market. Section 3 presents the modelling approach. Section 4 outlines the network features that we include in the empirical model. Section 5 introduces the empirical setting and the dataset. Section 6 discusses the main results. Section 7 concludes.

2 Structural features of the money market and the turmoil

The strategy adopted by the ECB in providing liquidity has been inspired by the assumption that the secondary market follows the rules of a perfect market. They are absence of price discrimination, of information asymmetry, and of dependence structures or preferential trading relationships with other banks. However, this hypothesis is fairly unrealistic. Also during stability periods, heterogeneity has been observed in the access to liquidity and in borrowing conditions. In respect to price discrimination and information asymmetry, the existence of market imperfections has been widely documented in several economic and econometric studies. Bolton, Freixas, and Shapiro (2004) prove the existence of asymmetric information, Idier and Nardelli (2008) estimate the probability of informed trading and, finally, Zagaglia (2010) shows that PIN is strongly priced.

With regard to counterparties selection and market structure, little is known. The few studies conducted so far, although rather preliminary, seem to point out the existence of distorsive behaviour. It has been observed that the banks do not behave all in the same way and that their actions are driven by specific strategies. Accordingly, banks are stated to carefully select their trading counterparties in the secondary market, following a preferential lending behaviour that does not aim strictly at profit maximization (see Cocco, Gomes, and Martins, 2009).

The main driver of bank lending or borrowing behaviour consists in market reputation. This effect is especially strong in an uncollateralized market, where lenders face the risk of not being repaid the principal. Lenders may also be unable to provide an adequate evaluation of credit risk (see Allen and Saunders, 1986). For these reasons, they assess the market reputation of potential counterparties before engaging in interbank trading. This implies that some banks can be rationed out of the market (see Furfine, 1999), or forced to face high borrowing interest rates (see Allen and Saunders, 1986; Furfine, 2001). From the perspective of market structure, these individual choices can generate a 'bottleneck problem' and lead the cash flow towards a small number of banks that are recognised as reliable. This mechanism is in line with the findings of Iori, De Masi, Precup, Gabbi, and Caldarelli (2008) who provide evidence of a skewed distribution in the number of trading counterparties.

A second driver for bank behaviour is related to the propensity for collaboration and clustering. The banking system is characterized by institutions with different balance-sheet size. In addition, there is a limited number of banks that enjoy access to the supply of liquidity offered by the ECB. Overall, there are banks that have systematic excess holdings of cash, and that act as net liquidity providers for the market. This behaviour takes the form of a tendency to build subgroups of trading partners over time, with which they cooperate or to which they lend on a stable basis. In line with this hypothesis, De Masi, Iori, and Caldarelli (2006) find evidence of an interbank market structure with groups of banks tightly connected to each other. [to be completed]

Market distortions that characterize periods of stability can increase in times of disruption. In a study of past financial crises, Goodhart (1987) suggests that severe market imperfections can be a consequence of greater uncertainty. Flannery (1996) claims that lenders become more uncertain about their own skills in assessing borrowers' creditworthiness. The outcome is that the lenders end up imposing high interest rates. Similar conclusions are drawn by Heider, Hoerova, and Holthausen (2009), who attribute the increase of interbank rates during the recent market turmoil to adverse selection.

3 Methodology

3.1 A descriptive overview of the modelling approach

In order to map the interbank market structure,a large array of recent studies have applied tools from social network analysis (see Bech and Atalay, 2008; Iori, De Masi, Precup, Gabbi, and Caldarelli, 2008). According to this methodological perspective, the interbank market is conceived as a network $N(V, E)$ whose nodes V are the banks, and ties E represent the money lent from bank i to j. These contributions discuss the main topological properties of the Euro money market [to be completed].

The available studies demonstrate the effectiveness of a methodological approach that is rarely applied to economic problems. However, they are concerned with commenting the descriptive patterns of cross-sectional data. In this sense, they disregard the determinants of the matching process between counterparties. In this work, we suggest that a longitudinal perspective on interbank networks can provide understanding on the strategic motives behind counterparty selection by banks. Our approach also considers the distortions induced by this search process.

We use a recently developed family of stochastic actor-oriented models - SAOM hereafter - of network dynamics that is specifically designed to study relational changes (see Burk, Steglich, and Snijders, 2007). This class of models has been originally introduced for applications in the field of social relations - i.e. relations among individuals -, but have been used also in studies on relations between organizations.

The aim of SAOM is to match the empirical features of network panel data, namely repeated observations of a social network for a given set of actors. SAOM represent empirically-observed changes in social relations as time-aggregated outcomes of micro mechanisms that determine tie formation (see Steglich, Snijders, and Pearson, 2010).

3.2 A technical outline of SAOM

We model a binary directed network variable $x(t)$ for a set $I = \{1, ..., n\}$ of actors. A relationship W is identified by a binary adjacency matrix $X(t)$. Each element x_{ij} denotes a tie variable that takes a value $x_{ij} = 1$ if i sends a tie to j, and $x_{ij} = 0$ otherwise. We regard the network ties as states, and not as events, with a tendency to endure over time.

Our modelling framework is based on the following building blocks:

- Changes in network ties are generated by an unobserved process with continuous underlying time paramter $t \in T$ over an interval $T = [t_1, t_M]$, and $T \subset R$. We assume that the network is observed at $M \geq 2$ discrete points in time or states. This formulation is in line with previous methodological contributions, and generates a parsimonious representation of the process driving the network dynamics (e.g., see Holland and Leinhardt, 1977; Runger and Wasserman, 1979).

- A continuous-time Markov process determines the change in network ties. For a given time $t_a \in T$, the conditional distribution for future values $\{X(t) : t > t_a\}$ given the past $\{X(t) : t \leq t_a\}$ depends only on $X(t_a)$. From the general theory of Markov chains, there exists a transition rate or intensity matrix Q where $q(x, y)$ describes the rate at which $X(t) = x$ tends to transition into $X(t+dt) = y$ as $dt \to 0$. Using a parsimonious notation, since

$$q_{ij}(x) = \lim_{dt \to 0} \frac{P\left\{X(t+dt) = x^{(\pm ij)} \mid X(t) = x\right\}}{dt} \tag{1}$$

with $i \neq j$, we can write

$$q_{ij}(x) = \lambda_i(x) p_{ij}(x) \text{ with } i \neq j \tag{2}$$

The term $\lambda_i(x)$ is the rate at which actor i has the opportunity to make a change in her outgoing ties. Also, $p_{ij}(x)$ denotes the probability that i changes x_{ij}.

- Actors have full information about the network structure. They send ties to their counterparties on the basis of other actors' attributes and their own position in the network.
- At a randomly-determined time t, actor i has the opportunity to change one tie variable x_{ij} only, or to take a 'microstep'. The frequency of micro steps is determined by a rate function. This means that the network change process is decomposed into a sequence of microsteps, with a network update consisting of a one-tie variation. When a micro step takes place, the probability distribution of the resulting outcome depends on the objective function.

Given the earlier discussion, T=the actor-based network change process is decomposed into two stochastic sub-processes:

- The change opportunity process, which models the frequency of microsteps. This frequency depends on stochastic-waiting times until the next opportunity, with expected values determined by a 'rate function'. The rate function $\lambda_i(x)$ for the time period $t_m \leq t < t_{m+1}$ takes the form

  $$\lambda_i(x) := \lambda_i\left(\rho_m, x, a, m\right) \tag{3}$$

  where $i \in I$, $x \in X$, ρ_m is a time-varying factor for period $m = 1, ..., M-1$, and a denotes a parameter dependent on either individual or network characteristics denoted as v.

  We model the rate function as dependent on actor-level covariates and structural properties of the current network state. We assume that the waiting times have a negative exponential distribution. Hence, the parameters are subjected to an exponential transformation, and

  $$\lambda_i(x) = \rho_m \exp\left(\sum_h a_h v_{hi}\right) \tag{4}$$

- The change determination process, which models the preferred direction of tie change. The objective function is a linear combination of a set of components called 'effects':

  $$f_i\left(\beta, x\right) = \sum\nolimits_{k=1}^{L} \beta_k s_{ik}\left(x\right) \tag{5}$$

  where $i \in I, x \in X$ denotes the outcome space, and L is the number of effects. The terms s_{ik} denote the so-called 'effects'. These consist of statistics of i's neighbourhood in x. The parameters β_k are weights that indicate the strength of s_{ik} while controlling for other effects.

The change process can also be interpreted as the outcome from the maximization problem of We assume that actor i selects the optimal counterparty j by maximizing the function

$$U = f_i(\beta, x^{(\pm ij)}) + U_i(t, x, j) \tag{6}$$

where $x^{(\pm ij)}$ represent an incoming - with a plus sign - or outcoming - with a minus sign - tie for i from j. The term $U_i(t, x, j)$ denotes a random disturbance that follows a Gumbel distribution. This is the so-called 'myopic stochastic optimization' of multinomial logit models (e.g., see Maddala, 1983). Conditional on actor i being allowed to make a change, the probability that x_{ij} changes into $1 - x_{ij}$ within the set C is equal to

$$p_{ij}(\beta, x) = \frac{\exp\left(f_i\left(\beta, x^{\pm ij}\right)\right)}{\sum_{x \in C} \exp\left(f_i\left(\beta, x^{\pm ij}\right)\right)} \tag{7}$$

To account for the dynamics of network structures, we consider an extension of the time-homogeneous model. We allow the model parameters β_k to be time heterogeneous (see Lospinoso, Schweinberger, Snijders, and Ripley, 2011). In this framework, we assume that the behaviour of interest can change across time. From a formal viewpoint, the objective function is modified in the following way:

$$f_{ij}^{(a)}(\beta, x) = \sum_{k=1}^{L} \left(\beta_k + \delta_k^{(a)}\right) s_{ik}(x) \tag{8}$$

where $\delta_k^{(a)}$ is the time dummy interacted effect parameter for effect k and period a. We define the vectors $\delta_k = \left(\delta_k^{(2)} ... \delta_k^{(|W|)}\right)$ and $\delta = \left(\delta_1 ... \delta_{|k|}\right)$. Equation 8 defines network changes during period W_a. Let us denote the observation period as the base period. We also assume $\delta_k^{(1)} = 0$ for all $k \in K$. This implies that the vector of time-dummy interacted-effect parameters δ has length $(|W| - 1)|K|$. For each effect included into the model and for each wave, $\delta_k^{(a)}$ indicates the direction and strength of the effect parameter variation around its long-term estimate.

3.3 Model estimation

Following Snijders (2001), we estimate the model through the Method of Moments - MoM. A suitable statistic $Z = (Z_1, \ldots, Z_k)$ of network activity should be chosen such that $\mathrm{E}_\theta(Z_k)$ is a monotonic function of θ_k. We then determine the value $\widehat{\theta}$ for $\theta := (\rho, \beta)$ such that the expected value of the statistic is equal to the observed value:

$$E_{\hat{\theta}}[Z] = z \tag{9}$$

A sensitive statistic for conditional estimation of $\theta_1 = (\rho_{t_1}, ..., \rho_{t_{M-1}})$ is based on the observed number of differences between successive observations

$$C = \sum_{\substack{i,j=1 \\ i \neq j}}^{n} |X_{ij}(t_{m+1}) - X_{ij}(t_m)| \tag{10}$$

For the weights $(\beta_1, ..., \beta_L)$ in the objection function, a suitable statistic takes the form

$$S_k = \sum_{i,j=1}^{n} s_{ik}(X_{ij}(t_{m+1})) \tag{11}$$

Since the moment equations cannot be solved analytically, the estimation for the MoM relies on Markov Chain Monte Carlo simulations of the network change process. This procedure is based on a stochastic approximation algorithm of Robbins and Monro (1951). It is based on the basic principle that the first observed network can be used only as a starting point for the simulations and need not be modelled. Based on experimental evidence on the MoM, the simulation process is based on 5,000 networks and 6 subphases.

3.4 Model testing

We test for alternative statistical hypotheses of model specification using a generalization of the score-type test proposed by Schweinberger (2007). Given the restricted model parameters $\theta_0 = (\beta, 0)$ and the corresponding unrestricted model parameters $\theta_1 = (\beta, \delta)$, the score statistic test is defined as:

$$\eta_U = U\left(\hat{\theta}_0\right)^T i^{-1}\left(\hat{\theta}_0\right) U\left(\hat{\theta}_0\right) \tag{12}$$

The test statistic η_U is asymptotically distributed χ^2. As an advantage, η_U requires the expected information matrix $i(\hat{\theta}_0)$ and the score function $U(\hat{\theta}_0)$, but not the estimates for the unrestricted model.

We adopt an iterative forward-selection strategy for the choice of the effects in the time-homogeneous model. The same approach is applied to the selection of time-dummy interacted effects in the time-heterogeneous model. This algorithm is originally proposed by Lospinoso, Schweinberger, Snijders, and Ripley (2011) and consists in the following steps:

1. estimate the parameters $\theta_0^\dagger$ of an arbitrary restricted model using the MoM;

2. denote by $\delta^\dagger$ the vector of parameters that are zero in the restricted model, and which we would like to test for statistical significance. We can then test the composite hypothesis:

$$\begin{aligned} H_0^{(J)} &: \delta^\dagger = 0 \\ H_1^{(J)} &: \delta^\dagger \neq 0 \end{aligned} \tag{13}$$

3. If $H_0^{(J)}$ is rejected, we select one $\delta_k^{(w)} \in \delta^\dagger$ to include in the model, and test the following:

$$
\begin{aligned}
&H_0^{(ak)} : \delta^\dagger = 0 \\
&H_1^{(ak)} : \delta^\dagger \neq 0, \text{ and } \delta_c^{(b)} = 0 \text{ for all } (c,b) \neq (k,a)
\end{aligned} \tag{14}
$$

4. evaluate the one-step estimators $\hat{\theta}^*$ and check which $\hat{\delta}_k^{(a)}$ has the largest magnitude;
5. select one $\hat{\delta}_k^{(a)}$ using the hypothesis test results for all the combinations (k,a) simultaneously, the one-step estimators for inclusion and
   - remove $\hat{\delta}_k^{(a)}$ from $\delta^\dagger$, add $\hat{\delta}_k^{(a)}$ to the restricted model, and return to step 1,
   - or end loops when we fail to reject H_0^j.

To assess the overall goodness of fit of the model, Lospinoso (2011, p. 76) suggests to calculate auxiliary statistics of networks. These statistics are not explicitly parameterized by any model effects. However, they are related to important features of the network through the probability model. The comparison between the values of the statistic computed on the estimated networks and those based on the networks generated in the simulation process should allow to assess the capability of the model to reproduce the evolution of the observed network data. For this purpose, we use the Monte Carlo Mahalanobis Distance Test described in Lospinoso (2011). Our auxiliary statistics include both indegree and outdegree, the triad census and the geodesic distance. [to be completed]

4 Network effects included in the model

We model both the rate and the objective function. The parameters of the rate function represent the average number of changes in network micro-steps between observation points. We assume that the rate of changes is not constant over time, and that it depends on actor characteristics. Table 1 outlines the types of effects included in our SAOM.

The frequency of changes is a function of outdegree, the tendency to have outgoing ties - i.e. to lend to other banks - and to indegree, the tendency to have incoming ties - i.e. to borrow from other institutions. This allows us to capture the tendency for banks to have more opportunities for changing their behaviour as their level of involvement (i.e. selecting partners or being selected as counterparties) grows.

The network objective function depends on a combination of different metrics that measure the direction of changes. These metrics consist of both endogenous and exogenous network effects. Endogenous effects represent patterns of tie formation arising from self-organizing patterns in local network structures. Exogenous-selection effects are instead associated with individual and dyadic attributes.

Table 1: Effects included in SAOM

(a) Rate function		
		Outdegree
		Indegree
(b) Objective function		
Endogenous effects	*Basic local effects:*	Outdegree
		Reciprocity
	Target effects:	Indegree popularity
		Out-in degree assortativity
		Transitivity
		Three-cycle effects
		Outdegree activity
Exogenous effects	*Control effects:*	Ego effect
		Alter effect
		Similarity effect

With regard to endogenous effects, we first control for a set of basic local structures. Outdegree looks at the degree of dyadic connection. Empirical estimates of outdegree typically have a negative sign, since actors tend not to build ties with anyone within their network. Reciprocity denotes the propensity to engage in ties with sign opposite to the existing one with the same counterparty. In this study, it can be interpreted as the tendency to lend to banks from which loans were previously received. Thus, it implies the existence of relations based on mutual aid.

We control for the so-called 'target effects', namely effects that are used to test for our research hypotheses. Indegree popularity formalizes the idea that the actors with the best reputation in the market can capture a large share of money flows. This is related to the 'preferential attachment phenomenon' of Barabasi and Albert (1999), which suggests that that actors who receive a large number of ties become more popular over time and continue to receive an increasing number of ties. Hence, being chosen as partner by many banks signals banks' capability to repay the loans received, therefore leading other actors to trust and lend to them.

We also consider a more complex specification of the reputational effect denoted as out-in degree assortativity. This reflects the preference of actors with high outdegrees for ties to actors with high indegrees. Therefore, this effect suggests the existence of a direct link between more active and more reliable actors, with the latter absorbing the liquidity made available by the largest lenders.

The tendency toward the creation of cohesive cooperative subnetworks is captured as a combination of transitive triplets and three-cycle effects. Transitive triplets represent network closure as driven by transitive triadic patterns of relations. For instance, if bank A lends to bank B, and bank B to bank C, then bank A will overcome the undirect relation and lend to C directly. Transitivity closure is the mechanism most frequently observed in empirical papers on interorganizational networks. It can be seen as the outcome of a redundancy principle, and may serve as insurance against disruption of flows and increase of uncertainty.

The three-cycle effect refers to cyclic closure. The three-cycle effect implies that if bank A lends to bank B, and bank B lends to bank C, then bank C will lend to bank A. The presence of cyclic closure can be interpreted as generalized exchange of resources (e.g., see Bearman, 1997). Tendencies against three-cycle represent aversion both for local hierarchy, and for resource dependence on other actors.

Finally, we control for the effect of outdegree activity. This consists of a self-enforcing effect that measures the propensity of active actors - i.e., those with higher outdegree - to form an increasing number of ties over time. Therefore, this effect captures the emergence of so-called 'key players' on the lending side of the market, namely banks that are large liquidity providers to the banking system.

The exogenous effects are related to the financial capability and excess cash holdings of banks. Since a SAOM is defined for binary networks only, the amount of liquidity lent can be specified as an individual attribute. The intuition for the ego effect is straightforward. It tests whether actors with high values of the attribute send ties to an increasing number of banks. In our study, this effect mimics the propensity of large lenders to have many counterparties.

The alter effect captures the propensity for actors with high values of the attribute to be chosen as a counterparty by a large number of banks. Typically we would expect the estimated sign on this effect to be negative. This would indicate that the lenders depend on many counterparties. If a positive value was estimated, it would point to a reinforcement effect, whereby most ties are drawn by the larger lenders. In this case, we would conclude that the interbank market is controlled by large banks in the both directions. Finally, the similarity effect looks whether ties tend to occur more often between banks with similar values of the attribute.

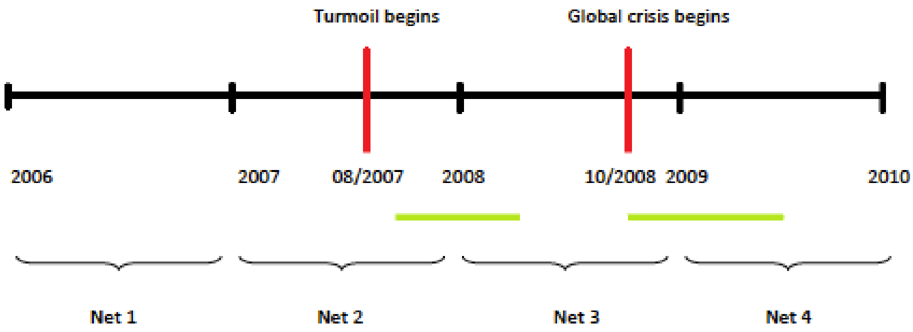
5 The dataset

The data used in this study are extracted from the Electronic Market for Interbank Deposits repository. This is an electronic market based on a specific trading platform. Hence, our dataset includes all the transactions occurred in the market among the registered banks.

To date, e-Mid includes 244 registered members. There are 138 Italian and 106 foreign banks. Despite covering around 20% of the interbank market, e-Mid has been stated to be well representative of the whole market dynamics (see Beaupain and Durre, 2010).

In the 'bid' or buy side of the market, transaction are started by the aggressor, who borrows from the quoter. In the 'ask' or sell side, transactions are also initiated by the aggressor, who lends to quoter. The amount exchanged and the interest rate are proposed

Figure 1: Periods included and model waves



by the actor that starts the trade. The agreement of the other bank is required for the transaction to take place. Moreover, banks can choose their trading counterparties, whereas the information on rates and amounts is made public. E-Mid is not a collateralized market. In this sense, it provides an ideal setting for observing patterns of counterparty selection. Finally, the market involves contracts with maturity structures ranging from overnight to twelve months. However, the largest share of trades - around 80% - occurs for overnight maturity.

For each transaction executed in the system, a string of data is produced. It provides information on the identity of both the aggressor and the quoter, on their nationality, the transaction size, the interest rate, the date and time of delivery, the loan length and the type of transaction - i.e., whether it is initiated by the ask or the bid side. Because of privacy concerns, the identity of each e-Mid member is represented by a unique six digit code. No other individual attributes are available to the public.

5.1 Data treatment

The observation period goes from January 2006 to December 2009. The sample includes 194 banks, active over the sample. Since no information is available about the exact time when a bank joins e-Mid, we assume that all the 194 banks are members from the beginning of the sample period. We assume that their absense indicates inactivity.

We use the information on the direction of cash flows to classify the aggressors and quoters as lenders and receivers. A tie exists from bank i to j when i lends money to j, indipendently from who starts the transaction. In particular,

1. for ask (sell) transactions, the tie goes from the aggressor (lender) to the quoter (borrower);
2. for bid (buy) transactions, the tie goes from the quoter (lender) to the aggressor (borrower).

The transactions from bank i to j are aggregated over a convenient time span. For the estimation of the model, we divide the 2006-2009 sample into subperiods of one year each,

Table 2: Network descriptive statistics

Network statistics	2006	2007	2008	2009
Av. indegree (st.dev.)	25.79 (32.59)	25.60 (32.67)	20.28 (28.70)	14.27 (22.92)
Av. outdegree (st.dev.)	25.79 (29.12)	25.60 (29.27)	20.28 (20.11)	14.27 (17.71)
Number of ties	5003	4966	3934	2768
Reciprocity	0.28	0.28	0.24	0.16
Transitivity	0.57	0.6	0.59	0.58
Isolates	11.00%	12.00%	19.00%	29.00%

and compute the adjacency matrix matrices $X(t)$ on annual data. Here we choose a time length that is long enough to identify stable relations and a network structure between banks. Our investigation is not concerned with short-term patterns or reactions to events at a daily frequency. In this sense, our approach to the construction of the dataset is consistent with the aim of modelling states rather than events.

In the construction of the time dummies, we follow Drudi, Durre, and Mongelli (2012) and isolate three periods of interest that underlie relevant market conditions. These are reported in Figure 1. We can idenfity a period of stability in the money markets that lasts until August 2007. The beginning of financial turbulence can be traced to August 2007. Finally, the shift from turmoil to global crisis took place in September 2008, and corresponds with the bankruptcy of Lehman Brothers.

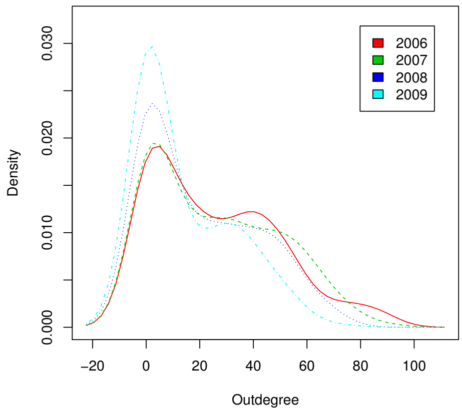
The three phases characterizing the path towards money market freeze have witnessed different degrees of policy involvement by the major central banks. In particular, the ECB has gradually introduced interventions aimed at counteracting the growing turbulence in financial markets. In order to account for policy-induced factors and for their impact over the structure of transactions, we do not cut the sequence of transactions at the end of August 2007 and September 2008, but two months later. We believe this allows for a time interval long enough to clear out the short-term effects of policy actions.

For every year of our sample, we build one 194×194 directed network. The value w_{ij} of the tie from i to j represents the amount of money that i lends to j over one year. Since SAOM is specified only for binary relations, the ties are dichotomized. We consider various alternative rules to construct the dichomotous matrix, such as the selection of the overall median as cut-off value, of the overall mean, and of the value 0. For the basic effects of our model, the estimation results are largely unaffected by the dichotomization criterion chosen. In this paper we intend to focus on the process leading to counterparty selection, rather than on the intensity of collaboration. Hence, we code the networks using a least restrictive criterion, and set all the tie values to 1 for $w_{ij} > 0$.

5.2 Descriptive statistics

Table 2 reports some descriptive statistics on the interbank networks. They all exhibit considerable fluctuations over time. The estimated networks for 2006 and 2007 have similar properties. In 2008 and 2009, the number of active banks significantly decreases. The number

Figure 2: Kernel density plot for network degree densities



of ties per actor - the so-called the average degree - drops sharply from 2008 to 2009. This indicates the progressive freezing of lending relations in the interbank market.

The outdegree distribution displays a bimodal shape, as shown by the kernel density estimate reported in Figure 2. Although there are many banks that concentrate their lending activities, the market is also characterized by a smaller and yet high number of institutions lending to many counterparties. Stability of networks over time between consecutive observations is assessed by looking at the Jaccard coefficients. [to be completed] Their values are equal to 0.555, 0.487 and 0.484 for each period.[1]

The average amount traded changes dramatically over time. The decrease in the average amount either lent or borrowed per bank is small between 2006 and 2007, and then it rises sharply. The amount lent decreases first from 14,101.51 euros to 12,079.71. It then falls to only 556.20 in 2008 and 379.32 in 2009.

In this paper, we use the net amount lent annually v_i as an individual attribute. For each bank i, v_i is computed as the difference between the average amount lent and borrowed:

$$v_i = \sum_{j=1}^{n} w_{ij} - \sum_{j=1}^{n} w_{ji} \tag{15}$$

The four distributions are then dichotomized at the mean value. The value 1 represents banks with an 'above normal' excess net lending, and the value 0 identifies 'below normal' cash balances. These distributions are included in the model as individual changing covariate, as their value is allowed to change between periods. The percentage of zeros is equal to 50% in 2006 and 2007, and to 51% in 2008 and 2009. The percentage of changes both from 1 to 0, and from 0 to 1 is 13% in period 1, 21% in period 2, and 20% in period 3.

[1]These figures are well above the 0.3 threshold value required for the estimations to converge.

6 Results

Our analysis is structured as follows. First, we estimate the restricted model, which accounts for the exogenous actor-specific covariate and for the endogenous network effects. We then estimate the full (unrestricted) model, which verifies the existence of time heterogeneity for all the effects. In estimating both models, we adopt the forward-selection approach discussed earlier. We add the effects one by one, each time checking for statistical significance of the parameter estimates before fitting embedding models. We start with the basic effects and, then, include the target effects first, and the control effects subsequently. Time dummies are tested after modeling each set of effects and added, when significant. We conclude with the goodness-of-fit checks for both the restricted and the unrestricted models.

Table 3 reports both the parameter estimates and standard errors for the selected effects. The estimated coefficients are not standardized. Convergence t-ratios for all the estimated parameters are smaller than the required threshold, i.e. 0.1 in absolute value (see Snijders, van de Bunt, and Steglich, 2010). 'Period 1' spans from January 1 2006 to June 30 2007, whereas 'period 2' goes from July 1 2007 to October 31 2008. The rest of the sample is denoted as 'period 3' . Since the restricted model is instrumental to the final one, we comment on the latter.

Panel (a) of Table 3 includes the estimated parameters for the rate function. The rates of network change show how frequently banks have the opportunity to make a change in their lending relations, either by engaging in new trades or by stopping trading relations in any period. The figures for this indicator are very high. For instance, it is equal to 15.514 for the first subsample - i.e. period 1 -, which is characterized by stable market conditions. A similar rate is observed for period 3, when interbank activity has frozen. The probability for a change in network structure reach a peak in period 2, as the global financial crisis starts. The estimated coefficients on both outdegree and indegree effects for the network change rate are positive. This suggests that banks trading with a large number of counterparties have more opportunities to change their partners.

The estimated parameters for the objective function are shown in Panel (b) of Table 3. The coefficient for outdegree carries a statistically-significant and negative sign. This indicates that lending is a rare event, and that banks are more likely to decide not to lend to institutions outside their network. The probability to lend to an institution that is not already a counterparty against the decision to not to lend is equal to $\exp(-2.900) = 0.055$. The intuition for this finding is straightforward. Lending to banks with which there are no existing ties generates additional exposure to credit risk that might be difficult to understand or quantify. In phases of market disruption when idiosyncratic risk can become systemic, the existence of a relationship may represent a determinant factor to control for the trustworthiness of a borrower. The positive and significant reciprocity effect indicates that banks have a tendency to build lending relations based on mutual support, and to lend to banks from which they have already borrowed. The probability for this to take place is equal to $\exp(0.730) = 2.075$.

Table 3: Parameter estimates for SAOM

	Restricted model	**Unrestricted model**
	Time homogeneity	Time heterogeneity
(a) Rate function		
Rate of net. change - period 1	15.498 (0.428)***	15.514 (0.453)***
Rate of net. change - period 2	18.152 (0.481)***	19.167 (0.541)***
Rate of net. change - period 3	15.365 (0.459)***	15.943 (0.478)***
Indegree for rate of net. change	0.012 (0.001)***	0.011 (0.001)***
Outdegree for rate of net. change	0.006 (0.001)***	0.007 (0.001)***
(b) Objective function		
Outdegree	-2.488 (0.056)***	-2.900 (0.067)***
period 2		-0.167 (0.035)***
period 3		-0.089 (0.034)***
Reciprocity	0.444 (0.038)***	0.730 (0.039)***
period 2		0.015 (0.055)
Transitive triplets	0.057 (0.002)***	0.051 (0.004)***
Three-cycles	-0.030 (0.002)***	-0.036 (0.002)***
Indegree popularity (sqrt)	0.060 (0.007)***	0.123 (0.015)***
Out-in degree assortativity	0.001 (0.005)	0.001 (0.005)
Outdegree activity (sqrt)	-0.002 (0.007)	0.002 (0.014)
Net amount lent ego	-0.174 (0.026)***	-0.032 (0.029)
period 2		-0.027 (0.061)
Net amount lent alter	-0.103 (0.025)***	-0.082 (0.029)**
period 2		-0.060 (0.049)
period 3		0.026 (0.056)
Net amount lent similarity	-0.041 (0.021)	-0.136 (0.025)***

Note: Two-sided tests. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$

The target effects included in the unrestricted model are all statistically significant. The positive parameter for indegree popularity shows that the choice of trading counterparties is driven by a self-reinforcing tendency. Banks that borrow from many counterparties demand liquidity from further banks outside their networks. Given the transparency of exchanges in e-Mid, this suggests that banks tend to borrow from institutions that are already trading with many institutions. Overall, these findings confirm the role of a selection-effect mechanism based on market reputation. The odds to form a tie with a bank that is already borrowing from many institutions are equal to $\exp(0.123) = 1.131$. On the other hand, we do not find any evidence for a 'rich club' phenomenon, whereby the most active lenders are largely tied to the most popular borrowers. In fact, the parameter estimate for out-in degree assortativity is not statistically significant.

Our results show that complex local structures matter in e-Mid. The combination of a positive transitivity effect and a negative coefficient for the three-cycles effect suggests that the network is characterized by local hierarchical ordering. Consistently Liberati, Marzo, Zagaglia, and Zappa (2012), we show that there are key actors that exert their influence over the rest of the market. In this type of hierarchical structure, the key institutions are large net lenders and behave as 'local central banks'. Over time, they build their own subnetworks and distribute their excess liquidity to the banks belonging to it. All else given, the probability to form a tie between two banks that close a transitive triplet is equal to $\exp(0.051) = 1.052$. By contrast, the odds for closure of a three-cycle are $\exp(-0.036) = 0.965$. This indicates that the formation of a hierarchical triangle is relatively more likely than that of alternative structures.

The remaining endogenous effect concerns outdegree activity. The negative estimated coefficient suggests that banks engaged in more transactions tend to decrease their activity over time. As the turmoil becomes stronger and market conditions worsen, banks set a limit to the maximum number of counterparties they lend to. However, this effect has a small size and is not statistically significant.

Our model includes actor-specific covariates. Interestingly, all the parameter estimates for the three effects related to net lending have a negative size. Since both the alter and the similarity effects are related to the net cash imbalance of a bank, the negative sign on their estimated coefficients have obvious implications. The alter effect indicates that, controlling for outdegree, large lenders are less likely to be also borrowers. This mechanism is reinforced by the similarity effect, which suggests that ties are most likely to occur between banks with different lending propensity. The probability of a transaction increases when a net lender trades with a net borrower. This suggests that a clear division of roles between borrowers and lenders tends to emerge over time. The interpretation for the negative estimated sign of the ego effect is less straightforward. The finding that frequent lenders supply liquidity to a restricted number of counterparties points to a trade-off between the amount lent and the number of trading counterparties.

The estimates of the time-heterogeneity parameters are not statistically significant for any of the target effects. There are two possible explanations for this. The first one is that there is a trend towards an increasingly strategic behaviour of market actors. However, this effect weakens over time. The negative parameter estimates for outdegree in periods 2 and 3 indicate that the pressure against the creation of new ties increases when the crisis becomes more severe, and the ECB intervention starts.

The time-heterogeneous parameter estimates can be computed as the sum of the overall coefficient and the time-dummy terms. For the outdegree effect, these figures are equal to -3.067 for period 2 and -2.989 for period 3. The probabilities are equal to $\exp(-3.067) = 0.047$ and $\exp(-2.989) = 0.050$, respectively. This is consistent with the freeze in interbank market activity after August 2007.

The estimated time-dummy coefficient for the reciprocity effect has a positive sign, although it is not statistically significant. This indicates that the propensity to establish mutual support in interbank relations increases throughout the sample. In other words, the division of roles between lenders and borrowers becomes weaker. The probability to take the other side of new ties with counterparties already involved in relations is equal to $\exp(0.745) = 2.106$.

The time dummies for the alter effect in periods 2 and 3 have opposite signs. The tendency for banks with less excess liquidity to attract a large number of counterparties is strong in period 2, and drops largely in period 3. A similar pattern holds for the ego effect. The probability for large lenders to find additional counterparties is equal to $\exp(-0.059) = 0.943$. This implies that these institutions are open to further outgoing ties in 2007-2008. Finally, since the dummy terms for actor-specific covariates are not statistically significant, we cannot draw any conclusion on their effects.

7 Conclusion

[to be written]

A A taxonomy of indices for network effects

Density effect, defined by the outdegree:

$$s_{i1}(x) := x_{i+} = \sum_j x_{ij} \tag{16}$$

Reciprocity effect:

$$s_{i2}(x) = \sum_j x_{ij} x_{ji} \tag{17}$$

Indegree popularity (sqrt) effect:

$$s_{i3}(x) = \sum_j x_{ij} \sqrt{\sum_h x_{hj}} \tag{18}$$

Outdegree activity (sqrt) effect:

$$s_{i4}(x) = \sum_j x_{ij} \sqrt{\sum_h x_{jh}} \tag{19}$$

Transitivity effect:

$$s_{i5}(x) = \sum_j , h x_{ij} x_{ih} x_{jh} \tag{20}$$

Three-cycles effect:

$$s_{i6}(x) = \sum_j , h x_{ij} x_{jh} x_{hi} \tag{21}$$

Out-in degree assortativity effect:

$$s_{i7}(x) = \sum_j x_{ij} x_{i+}^{1/2} x_{+j}^{1/2} \tag{22}$$

Alter effect:

$$s_{i8}(x) = \sum_j x_{ij} v_j \tag{23}$$

Ego effect:

$$s_{i9}(x) = v_i \sum_j x_{ij} \tag{24}$$

Similarity effect:

$$s_{i10}(x) = \sum_j x_{ij} \left(sim_{ij}^v - \hat{sim}^v \right) \tag{25}$$

B The implementation of MoM estimation

Suppose that at least 2 observations on $X(t)$ are available for observation moments t_1 and t_2. The estimation method conditions on $X(t_1)$ and makes no assumption about the stationarity of the network distribution. We can simulate realizations from the network and apply a version of the method of moments.

We choose a suitable statistic $Z = (Z_1, \dots Z_k)$, namely K variables that can be computed from the network. The statistic Z should be a monotonic function of the paramter vector θ. The method of moments pins down the estimates $\hat{\theta}$ for $\theta = (\rho, \beta)$ such that the observed and expected values of the Z statistic are equal:

$$\mathrm{E}_{\hat{\theta}}\left[Z\right] = z \tag{26}$$

The method of moments delivers the covariance matrix

$$\mathrm{cov}(\hat{\theta}) \approx D_{\theta}^{-1} \Sigma_{\theta} D_{\theta}^{\prime -1} \tag{27}$$

with

$$\Sigma_{\theta} = \mathrm{cov}\left(Z|X(t_1) = x(t_1)\right) \tag{28}$$

and

$$D_{\theta} = \frac{\partial}{\partial \theta} \mathrm{E}\left(Z|X(t_1) = x(t_1)\right) \tag{29}$$

The moment equations cannot be solved analytically or by using standard numerical methods. The reason is that $\mathrm{E}_{\hat{\theta}}\left[Z\right]$ cannot be computed explicitly. The solution is thus approximated through the method for stochastic approximation proposed by Robbins and Monro (1951). This is based on iteration steps with

$$\hat{\theta}_{N+1} = \hat{\theta}_N - a_N D^{-1}(z_N - z) \tag{30}$$

where z_N denotes a simulated value for Z with parameter $\hat{\theta}_N$, D is a suitable matrix, and $a_N \to 0$ is a parameter. The iteration rule 30 defines a Markov Chain under a set of stability conditions discussed in Snijders (2001). This is what makes the estimation method a Markov Chain Monte Carlo algorithm.

B.1 Estimation algorithm

The estimation process is made of three steps:

1. preliminary phase with estimation of $\partial \mathrm{E}_{\theta}[Z]/\partial \theta$ for defining D^0. Given a number n_1 of steps, for each step N:

   - generate indipendent vectors $Z_{N0} \sim \theta_1$ and $Z_{Nj} \sim \theta_1 + \epsilon_j e_j$, where ϵ_j is a suitable constant;
   - compute the difference quotients

     $$d_{Nj} = \epsilon_j^{-1}(Z_{Nj} - Z_{N0}) \tag{31}$$

- estimate $\mathrm{E}_{\theta_1}[Z]$ and $D(\theta_1)$, respectively, by

$$\hat{z} = \frac{1}{n_1} \sum_{N-1}^{n_1} Z_{N0} \tag{32}$$

$$\hat{D} = \frac{1}{n_1} \sum_{N-1} d_N \tag{33}$$

- make a Newton-Raphson step

$$\hat{\theta}_{n_1} = \theta_1 - \hat{D}^{-1}(\hat{z} - z) \tag{34}$$

- use the diagonal matrix $\bar{D} = \mathrm{diag}(\hat{D})$ in the following phase;

2. estimation phase with Robbins and Monro (1951) updates, where a_N remains constant in subphases and decreases between subphases. Given a number of subphases and iteration steps per subphase:

   - set a number of subphases and iteration steps per subphase;
   - for each subphase k:

     a. set a minimum n_{2k}^{-} and a maximum n_{2k}^{+} number of iterations:

     (a.1) the subphase ends at less than n_{2k}^{+} if the number of steps exceeds n_{2k}^{-},

     (a.2) the subphase terminates if n_{2k}^{+} is reached;

     b. at each iteration step within subphase N:

     (b.1) generate Z_N for a $\hat{\theta}_N$;

     (b.2) update $\hat{\theta}_{N+1}$ according to the Robbins and Monro (1951) formula;

     c. at the end of each subphase:

     (c.1) compute the average of $\hat{\theta}_N$ and use it as the starting value for the following subphase;

     (c.2) divide the previous value of a_N by 2 before entering a new subphase

   - continue between t_m and t_{m+1} until we reach the observed number of differences;

3. final phase where θ remains constant at the estimated value in the last period to:

   - check for convergence, i.e. $\mathrm{E}_{\hat{\theta}}[Z] \approx z$;
   - estimate D_θ and Σ_θ.

We should stress that the parameters do not change in periods between observations, except for the rate of change ρ which is given by ρ_m for $t_m \leq t < t_{m+1}$

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