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# A network analysis of the Italian overnight money market

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## Abstract

The objective of this paper is to analyse the network topology of the Italian segment of the European overnight money market through methods of statistical mechanics applied to complex networks. We investigate differences in the activities of banks of different sizes and the evolution of their connectivity structure over the maintenance period. The main purpose of the analysis is to establish the potential implications of the current institutional arrangements on the stability of the banking system and to assess the efficiency of the interbank market in terms of absence of speculative and preferential trading relationships.

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## 1. Introduction

In this paper we present an analysis of the European interbank market of overnight loans arising from liquidity requirements imposed by the European Central Bank (ECB). In order to prevent liquidity shocks,<sup>1</sup> the ECB requires that the reserves of any bank operating in the Euro zone, are deposited with the respective national central bank (NCB). Reserves are computed, once per month, as a proportion (2%) of the total deposits and debts owned by the bank. The one-month maintenance period runs from the 24th of a month to the 23rd of the following month (hereafter denoted as the end of month (EoM) day). Banks exchange liquidity with each other in order to satisfy the reserve requirements whilst minimising the implicit costs associated with this regulatory constraint. The set of internal loans and debts has a structure that can be naturally described by means of a network, that is a system consisting of vertices (banks) connected by one or more oriented edges (debts/loans). The aggregate characteristics of the entire set of transactions can thus be studied in terms of the statistical and topological properties of this network. This enables us to use well-established methodologies to assess the stability, self-organisation and redundancy of the various relationships between banks as well as the overall robustness of the financial system to external shocks.

Network analysis of economic and financial structures has already been applied in the context of associations between board of directors (Battiston et al., 2003), stock ownership networks (Garlaschelli et al., 2005) and graph representations of stock returns correlation matrices (Bonanno et al., 2003).

It is well known that the topology of a network (for example the Internet connectivity map, the World Wide Web, author collaboration networks, biological networks, communication networks, power networks) affects its functionality and stability (Albert and Barabasi, 2002; Newman, 2004). Purely 'random networks', (i.e. networks obtained by randomly drawing edges between pairs of vertices) are characterised by a degree (the number of links of a vertex) distribution that is peaked around a finite mean value, and has finite variance. In these structures no hubs are present and the system is resilient to targeted attacks. On the contrary scale-free networks (i.e. networks with a power law distribution of degrees) are extremely vulnerable to intentional attacks on their hubs (see Albert et al., 2000). Attacks that simultaneously eliminate a small proportion of the hubs can collapse a scale-free network. Nonetheless scale-free networks can heal themselves rapidly if an insufficient number of hubs are simultaneously removed. Scale-free networks are also extremely vulnerable to epidemics (Barthélemy et al., 2005). In random networks, epidemics need to surpass a critical threshold (a number of nodes infected) before they propagate system-wide. Below the threshold, the epidemic dies out. Above the threshold, the epidemic spreads exponentially. Recent evidence indicates that the threshold for epidemics on scale-free networks is zero.

The emergence of contagion and systemic risk in the interbank market and in payment systems has been extensively analysed (Angelini et al., 1996; Angelini, 2002;

<sup>1</sup>This is carefully explained in the next section.

Furfine, 2003; Iori and Jafarey, 2001; Iori et al., 2006; Boss et al., 2006). Iori et al. (2006) show that in a simulated model of heterogeneous trading banks, the network structure plays a crucial role in the stability of the overall system. The recent paper by Boss et al. (2006) investigates the network of overall credit relationships in the Austrian interbank market. In their study the authors analyse the liabilities for 10 quarterly single month periods, between 2000 and 2003, among 900 banks. They find a power-law distribution of contract sizes, and a power-law decay of the distribution of incoming and outgoing links (a link between two banks exists if the banks have an overall exposure to each other). Furthermore they show that the most vulnerable vertices are those with the highest centrality (measured by the number of paths that go through them).

A different issue has been explored by Cocco et al. (2003) who have investigated the nature of lending relationships in the fragmented Portuguese interbank market over the period 1997–2001. In fragmented markets the amount and the interest rate on each loan are agreed on a one-to-one basis between borrowing and lending institutions. Other banks do not have access to the same terms, and no public information regarding the loan is available. The authors showed that frequent and repeated interactions between the same banks appear with a probability higher than the one expected for random matching. In addition they found that during illiquid periods, and in particular during the Russian financial crisis preferential lending relationships increased.

Our paper focuses on the network analysis of the overnight maturity on the Market for Interbank Deposits (e-MID). This market is unique in the Euro area in being screen based and fully electronic (outside Italy interbank trades are largely bilateral or undertaken via voice brokers). While banks can still choose their trading counterparty, the information about the rates and the trades is made public. Our data set is composed of banks operating in the Italian market for which we have the complete record of transactions. For every day of trading we compute the network of debts and loans. We investigate differences in the activities of banks of different sizes and the evolution of their connectivity structure over the years and over the maintenance period. The main objectives are to understand the potential implications of the current institutional arrangements on the stability of the banking system and to assess the efficiency of the interbank market.

We find clear patterns of structural change over the years and during the maintenance period. We also find that the network structure is characterised by a degree (the number of links of a vertex) distribution that while not scale-free, is heavier tailed than a purely random network indicating that a few banks trade with many counterparties while the majority trade with a few. The system is in fact characterised by a small group of large banks borrowing from a large number of small creditors, a configuration that is particularly susceptible to systemic risk. Furthermore the current institutional settings push the system, as the EoM date approaches, towards a configuration that has even higher systemic risk potential.

We show that preferential lending is limited and money flows directly from the lender to the borrower without intermediaries. Banks seem unable to find short-term

profit opportunities by borrowing from some and lending to others on the same day. These observations suggest that the interbank market is relatively efficient.

The remainder of this paper is organised as follows. Section 2 explains the institutional arrangements and Section 3 describes the database. Section 4 explains how we construct the banking networks and discusses the measures we use to analyse them. In Section 5 we present the results and Section 6 has the conclusions.

## 2. Institutional arrangements for liquidity management in the Euro area

Liquidity management in the banking system is essential for the smooth operation of payments and in particular the real time gross settlement (RTGS) systems. The ECB normally aims to satisfy the liquidity needs of the banking system via its open market operations (main and long-term refinancing operations, fine-tuning and structural interventions) the most relevant of which are the weekly auctions. Until June 2000, auctions were executed at a fixed interest rate. Since then they have been conducted as variable rate tenders. The ECB decides in advance the minimum bid rate and the fixed amount of liquidity to be supplied through the auction. On Monday afternoons credit institutions present their bids to the respective NCBs. The NCBs submit the amount of money they want to deal and the interest rate they are prepared to accept. The ECB collects the bids on Tuesday mornings and executes the auctions. The allocations are settled on the banks' accounts with their NCBs on Wednesdays. The Eurosystem also offers credit institutions two standing facilities: the marginal lending facility for obtaining overnight liquidity from the NCB against the presentation of sufficient eligible assets; and the deposit facility for overnight deposits with the central bank.

Credit institutions in the Euro area are required to hold minimum reserve balances with NCBs (set at 2% of all deposits and debt issued with a maturity of less than two years, excluding repos and interbank liabilities, but with a minimum threshold applied). Reserves provide a buffer against unexpected liquidity shocks, mitigating the related fluctuations of market rates. They have to be fulfilled only on average over a one-month maintenance period that runs from the 24th of a month to the 23rd of the following month (if this is a holiday then it shifts to the previous working day). This feature of the framework has limited the overnight rates volatility without the need for Eurosystem fine-tuning operations. Reserve holdings under the minimum requirements are remunerated at the main refinancing rate but there is no interest paid for any excess reserves. Banks can exchange reserves on the interbank market in order to minimise their reserve costs.

Credit institutions make heavy use of this flexibility to average their reserves over the maintenance period. As a consequence, a monthly reserves pattern within the maintenance periods has emerged ([Bank of England Publications, 2000](#)). In general the market begins each reserve maintenance period in deficit, until the ECB provides sufficient liquidity with the first MRO (main refinancing operation) for that period. There are indications ([Bank of England Publications, 2000](#); [Gabbi, 1992](#)) that not all credit institutions actively manage their minimum reserves. Some, particularly small

institutions tend to keep their reserve account at the requisite level constantly throughout the maintenance period, although some might use the necessary amounts intra-daily to meet their need for payments system liquidity.

The stabilising effect of the averaging behaviour becomes weaker and eventually vanishes towards the end of the reserve maintenance period, when banks are no longer in the position to defer the fulfillment of their reserve requirements. This is well illustrated by the plot of overnight rates between January 1999 and December 2002 displayed in Fig. 1. On or shortly before the 23rd of each month, overnight rates exhibit either a sharp dip (excess liquidity compared to the required minimum reserve average) or a pronounced peak (shortage of liquidity).

The overnight rate is bounded from above and below by the official rates corridor fixed by the ECB: banks can borrow against collateral at the rate of the marginal lending facility (the ceiling) or deposit funds at the rate of the overnight deposit facility (the floor). Usually the overnight rate is above the main refinancing rate since the banking system is liquidity short, so that the ECB monetary policy is effective.

The highest drop in the overnight euro interest rate (EONIA) took place immediately after the terrorist attack on the 11th of September 2001 (time(day) index 690) when both the US Federal Reserve and the ECB decided to cut interest rates by 50 basis points whilst at the same time providing a large amount of liquidity. From November 2001 (time(day) index around 730) to the third quarter of 2002 the main refinancing rate has not changed from 3.25%. Consequently the interest rate volatility declines, with variations consistent with the monthly maintenance period pattern.

The intra-day and intra-maintenance period patterns in the European money market have been analysed in a number of papers. Both Hartmann et al. (2001) and Barucci et al. (2004) report an intra-day pattern for the number of contracts with a

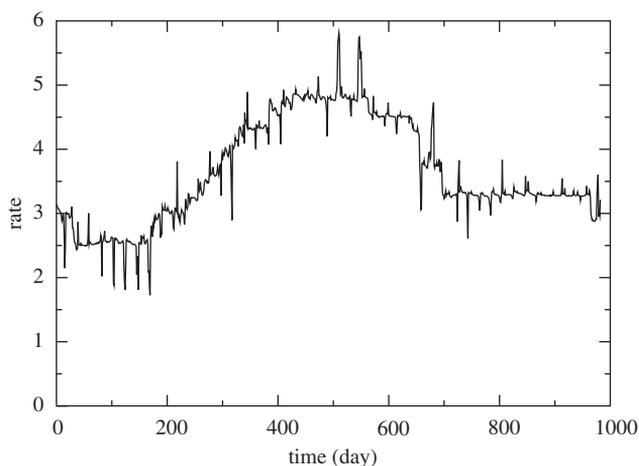


Fig. 1. Time series of daily interest rates from January 1999 to December 2002.

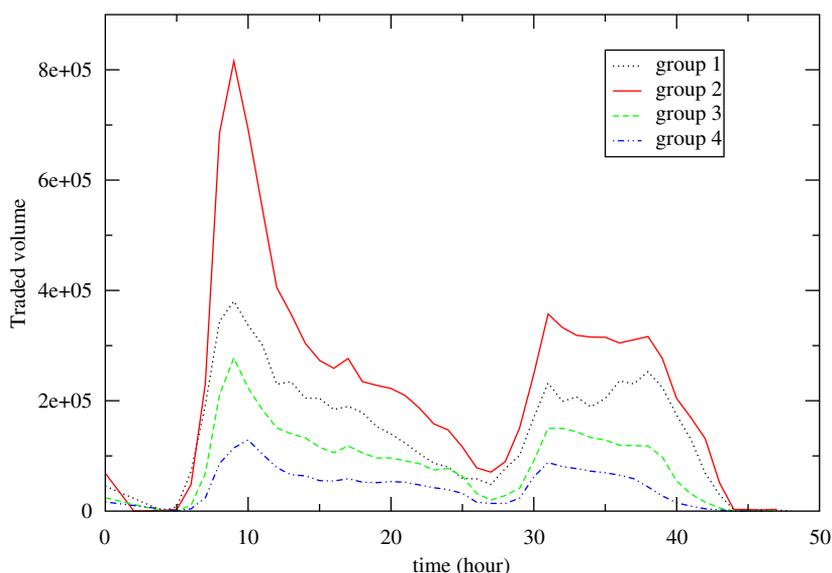


Fig. 2. Average intra-day pattern per group of banks, over the period 1999–2002; group 1 (black-dotted), group 2 (red-solid), group 3 (green-dashed), group 4 (blue-dotdashed).

bimodal profile, where the first peak in the middle hours of the morning is higher than the one in the afternoon. This pattern is shown in Fig. 2 for different categories of banks.<sup>2</sup>

The events that contribute to the above intra-day patterns have been identified as follows: around 9:00am pending payments of various nature are settled automatically, the bulk of which consists of previous day e-MID contracts; around 12:00am banks settle the balance of net payments; around 12:30pm banks settle the cash leg of the net security settlement system; in the afternoon banks mainly settle financial and interbank payments.

With regard to the intra-maintenance period patterns, Hartmann et al. (2001) have shown that quoting activity, spreads and rate volatility are very high on Thursdays, particularly during lunchtime when the ECB's interest rate decisions are released. They also report a short period of intense market activity without particularly large spreads after the auction, which suggests that the post-auction liquidity reallocation process through the interbank market is relatively efficient. They also show that spreads and volatility tend to be very high at the end of the minimum reserve maintenance period. Barucci et al. (2004) noticed a decline in exchange volumes and an increase in the number of contracts on the last few days of the maintenance periods. This pattern is shown in Fig. 3: we plot in red the amounts borrowed (left) and the number of transactions (right) per borrowing bank and in black the corresponding amounts per lending bank.

<sup>2</sup>The classification of banks in groups is given and explained in Section 4.

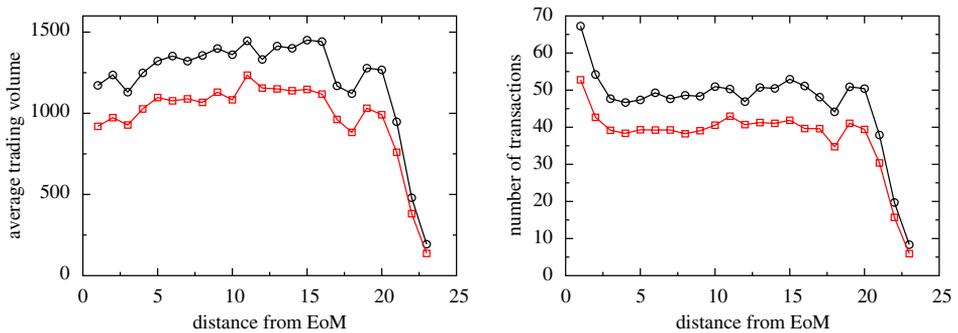


Fig. 3. Average daily trading volume (left) and daily number of transactions (right) over the period 1999–2002 for lending banks (black-circle) and borrowing banks (red-square).

### 3. e-MID and the data set

The Italian electronic broker market e-MID<sup>3</sup> covers the entire domestic overnight deposit market in Italy. Both Italian banks and foreign banks can exchange funds on the e-MID. The number of participating banks was 215 in 1999, 196 in 2000, 183 in 2001 and 177 in 2002. When an Italian bank is involved, settlement takes place in the Italian RTGS system BI-REL (the Italian component of the bank payments settlement system TARGET).

Trades are in Euro or USD for maturities between overnight and one year; 90% of the trades are overnight. Rates can be expressed in basis points or  $\frac{1}{16}$ th for the Euro and in basis points or  $\frac{1}{32}$ nd for the US dollar. The minimum quote is 1.5 million Euro and 5 million US dollars. Each quote is identified as either an offer or a bid. An offer indicates that the transaction has been executed at the selling price of the quoting bank while a bid implies that the quoting bank's buying price has been accepted. The names of the banks are visible next to their quotes to facilitate credit line checking. A quote is submitted and the transaction is finalised if the ordering bank accepts the listed bid/offer. When a bid rate is hit, the transaction can be executed automatically or manually within 90 s, if a bank prefers to first check the lending counterparty's name. For an offer rate hit the transaction needs to be accepted manually within 90 s to allow credit line checking. The market also permits bilateral trades with a chosen counterparty.<sup>4</sup>

Our data set consists of all the overnight transactions (586,007 in total) concluded on the e-MID from January 1999 to December 2002. For each contract we have information about the date and time of the trade, the quantity, the interest rate and the name of the quoting and ordering banks. The information about the parties involved in a transaction allows us to perform an accurate analysis of daily bank trading relationships and their evolution over time.

<sup>3</sup>e-MID is run by e-MID S.p.A. Società Interbancaria per l'Automazione (SIA), Milan. The central system is located in the SIA office and the peripherals on the premises of participating members.

<sup>4</sup>For more details see <http://www.e-mid.it/index.php/article/articleview/85/0/29/>.

#### 4. Network analysis

Given our data set, we can define three daily matrices: the adjacency matrix  $A$ , the connectivity matrix  $C$  and the weighted connectivity matrix  $W$ . The element  $a_{ij}$  of the adjacency matrix indicates whether a transaction between banks  $i$  and  $j$  has occurred during a given day (i.e.  $a_{ij} = 0$  if there is no transaction and  $a_{ij} = 1$  if at least one transaction has occurred). The elements  $c_{ij}$  of the connectivity matrix denote the number of transactions between banks  $i$  and  $j$  in a given day. The elements  $w_{ij}$  of the weighted connectivity matrix represent the overall volume exchanged between banks  $i$  and  $j$  in a given day. The number of active links in the network is defined as  $N_l = \frac{1}{2} \sum_{ij} a_{ij}$ , the number of transactions as  $N_t = \frac{1}{2} \sum_{cij} c_{ij}$  and the overall trading volume as  $V = \frac{1}{2} \sum_{ij} w_{ij}$ . We denote the number of active banks as  $N_b$ .

The three matrices,  $A$ ,  $C$ ,  $W$ , define non-directed graphs in the sense that the links are bi-directional with  $a_{ij} = a_{ji}$ ,  $c_{ij} = c_{ji}$  and  $w_{ij} = w_{ji}$ . Our data set also enables us to construct matrices associated with directed graphs. We can make links directional by allowing them to follow the flow of money, such that a link is incoming to the buyer and outgoing from the seller. A directed graph is more relevant if one is interested in assessing the risk of contagion and systemic default in the system. Hence we define six more matrices  $A^b, A^l, C^b, C^l$  and  $W^b, W^l$ . The elements  $a_{ij}^b$  ( $a_{ij}^l$ ) indicate whether at least one transaction has occurred on a given day between banks  $i$  and  $j$  with bank  $i$  as the borrowing (lending) bank. The elements  $c_{ij}^b$  ( $c_{ij}^l$ ) of the connectivity matrix denote the number of transactions on a given day between banks  $i$  and  $j$  with bank  $i$  as the borrowing (lending) bank. The elements  $w_{ij}^b$  ( $w_{ij}^l$ ) of the weighted connectivity matrix denote the overall volume exchanged on a given day between banks  $i$  and  $j$  with bank  $i$  as the borrowing (lending) bank. It is clear that  $w_{ij}^l = w_{ji}^b$ . We define the flow between two banks as  $f_{ij} = w_{ij}^l - w_{ij}^b$ . The flow is positive if the bank is a net lender.

Highly interconnected systems have been the focus of a great body of research in computer science, physics and the social sciences. The focus has recently shifted to weighted networks. A set of metrics combining weighted and topological observables has been proposed to characterise the statistical properties of vertices and edges and to investigate the relationships between the weighted quantities and the underlying network structures (Barrat et al., 2004; Newman, 2004; Dorogovtsev and Mendes, 2003). Some of the commonly used metrics are:

##### 4.1. Degree

The degree of a node is defined as

$$k_i = \sum_{j \in \mathcal{V}(i)} a_{ij}, \quad (1)$$

where the sum runs over the set  $\mathcal{V}(i)$  of neighbours of  $i$ , i.e.  $\mathcal{V}(i) = \{j | a_{ij} = 1\}$ . The in-degree  $k^b$  and out-degree  $k^l$  are defined as

$$k_i^b = \sum_{j \in \mathcal{V}(i)} a_{ij}^b, \quad k_i^l = \sum_{j \in \mathcal{V}(i)} a_{ij}^l. \quad (2)$$

In this context, the degree provides a measure of the number of counterparties a bank trades with (or lends and borrows in the case of directed networks). Random networks (i.e. networks where  $N$  nodes are connected at random with a given probability  $\phi$ ) are characterised by a Poisson distribution of degrees:

$$p(k) = \frac{e^{-\bar{k}} \bar{k}^{-k}}{k!},$$

where  $\bar{k} = \phi(N - 1)$  is the average degree. Real world networks are rarely purely random and the most commonly found distributions are either exponential  $p(k) \sim e^{-k/\bar{k}}$  or power-law  $p(k) \sim k^{-\gamma}$ . In the last case the network is called scale-free.

#### 4.2. Strength

A weighted network measure for each link (i.e. the size of trades on the link, or the number of times the link has been used) is obtained by measuring the *strength* of the relevant vertices.

We define the vertex weighted strength  $s_i^w$  as

$$s_i^w = \sum_{j \in \mathcal{V}(i)} w_{ij}, \quad (3)$$

and the vertex connectivity strength  $s_i^c$  as

$$s_i^c = \sum_{j \in \mathcal{V}(i)} c_{ij}. \quad (4)$$

We can also define the strength in terms of the vertex net flow as

$$f_i = \sum_{j \in \mathcal{V}(i)} f_{ij}. \quad (5)$$

Similarly we can define the borrowing and lending strengths as

$$s_i^{w,b} = \sum_{j \in \mathcal{V}(i)} w_{ij}^b, \quad s_i^{w,l} = \sum_{j \in \mathcal{V}(i)} w_{ij}^l, \quad (6)$$

and the equivalent expressions for  $s_i^{c,b}$  and  $s_i^{c,l}$ . The strength measures the overall transaction volume for a given bank (or the aggregate amount of borrowing and lending in the case of directed networks).

#### 4.3. Affinity

Affinity is a measure of similarity between nodes and is defined as

$$k_{m,i} = \frac{1}{k_i} \sum_{j \in \mathcal{V}(i)} k_j. \quad (7)$$

If  $k_{m,i}(k) = \{k_{m,i} | k_i = k\}$  is increasing with  $k$  then high-degree vertices are more likely to be linked to other highly connected nodes. This property is called *assortative mixing*. When  $k_{m,i}(k)$  decreases with  $k$  (*disassortative mixing*), high-degree vertices

have a majority of low-degree neighbours, whilst the opposite holds for low-degree vertices. In our case assortative mixing indicates that banks which have a large number of counterparties are more likely to be connected to other banks with a high number of trading partners.

#### 4.4. Clustering

The clustering coefficient  $\tilde{c}_i$  is a measure of connection density around vertex  $i$  and is defined as

$$\tilde{c}_i = \frac{2}{k_i(k_i - 1)} \sum_{j,h} a_{ij}a_{ih}a_{jh}. \quad (8)$$

The clustering coefficient represents the proportion of nearest neighbours of a node that are linked to each other. In our case, it indicates whether there is a link between two banks which have a common trading partner. The clustering coefficient measures the number of triangles in a system. In order to have a triangle in the payments system at least one bank must lend to one counterparty and borrow from another. The clustering coefficient provides us with a way to assess the extent of this kind of intermediary trading. The average clustering coefficient,

$$C = \frac{1}{N} \sum_i \tilde{c}_i,$$

is an overall statistical measure of the density of interconnected vertex triplets in the network.

#### 4.5. Diameter

In a graph the distance between two vertices is given by the length of the shortest path joining them (if it exists). In a connected graph the average distance is the average over all paths. If the graph is not connected, the average distance is defined as the average among all distances for pairs belonging to the same connected component. The diameter of a graph is given by the maximum of all distances between pairs. If the diameter of the banking network is substantially different from that of a random network it would indicate that there could be preferential paths for money flows between banks.

#### 4.6. Participation ratio

For a given node  $i$ , with connectivity  $k_i$  and strength  $s_i$ , the weights of the edges can either be of the same order of magnitude,  $s_i/k_i$ , or they can be heterogeneously distributed, with some edges dominating others. The participation ratio is defined as

$$Y_2^w(i) = \sum_{j \in \mathcal{V}(i)} \left[ \frac{w_{ij}}{s_i} \right]^2, \quad (9)$$

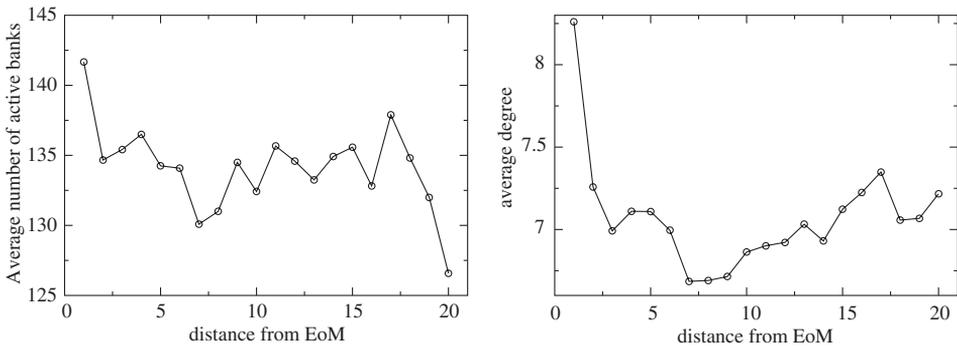


Fig. 4. Average number of active banks (left) and average degree (right) in 2002.

or equivalently

$$Y_2^c(i) = \sum_{j \in \mathcal{V}(i)} \left[ \frac{c_{ij}}{s_i^c} \right]^2. \quad (10)$$

If all the weights are of the same order of magnitude then  $Y_2 \sim 1/k_i$  but if a small number of weights are dominant then  $Y_2$  is close to 1. A participation ratio close to unity indicates preferential relationships between banks.<sup>5</sup> Similarly we can define the participation rates  $Y_2^{w,b}(i)$  and  $Y_2^{w,l}(i)$  separating incoming and outgoing links. The average participation ratio is then computed as

$$Y_2^w = \frac{1}{N} \sum_i Y_2^w(i), \quad Y_2^c = \frac{1}{N} \sum_i Y_2^c(i).$$

## 5. Results

In the following we focus on the structure of the banking network and its time evolution. The objective is to identify structural changes in the network over time, particularly close to the end of the maintenance periods, and to compare lending and borrowing patterns for different types of banks.

In Fig. 4 we plot the daily average number of active banks and daily number of active links as a function of the distance from the EoM (the distance is one on the EoM days). The figure shows that not only does the number of transactions increase towards the EoM, as previously shown in Fig. 3, but the number of active links and the number of trading banks rise too. This suggests that final adjustments to liquidity are achieved through a larger number of smaller-volume trades, involving a higher than usual number of counterparties. Barucci et al. (2004) interpreted this observation as a sign that banks manage their liquidity efficiently so that on the

<sup>5</sup>Note that the statistic used by Cocco et al. (2003) is the lender preference index (LPI) (and the corresponding borrower preference index) defined as  $LPI = (\sum_{i=1}^{30} w_{ij}^l(t)) / (\sum_{i=1}^{30} s_i^{w,l}(t))$ .

EoM days only small adjustments are necessary to the average reserve. Nonetheless, the higher number of banks trading on the EoM days is also compatible with a less optimistic interpretation: banks have less liquidity available to offer on EoM days so that borrowing banks need to engage in a higher number of transactions with several counterparties to collect, however possible, the liquidity needed to balance their reserves.

In Fig. 5 we compare the decumulative density function (DDF) of vertices' degrees and strength for the entire banking system in 1999 and 2002. The maximum degree is lower in 2002 for both incoming and outgoing links as a consequence of a number of mergers between banks which has reduced the number of e-MID members from 215 in 1999 to 177 in 2002. The figure provides clear evidence that the market has undergone a transition over time, moving from a situation in 1999 when large lenders dominated large borrowers, and outgoing links were more numerous than incoming links, to the opposite situation in 2002. These observations indicate that, over time, banks have started to trade with a larger number of counterparties when buying liquidity and a smaller number when selling it. A full explanation of this transition is not possible due to lack of complete information about the overall activities of banks. Nonetheless there are several possible explanations for the change from 1999 to 2002. The Italian economy has been on a growing trend until mid 2000 and since then the GDP growth rate decreased until the end of 2002. During periods of strong GDP growth the smaller banks and those located in less

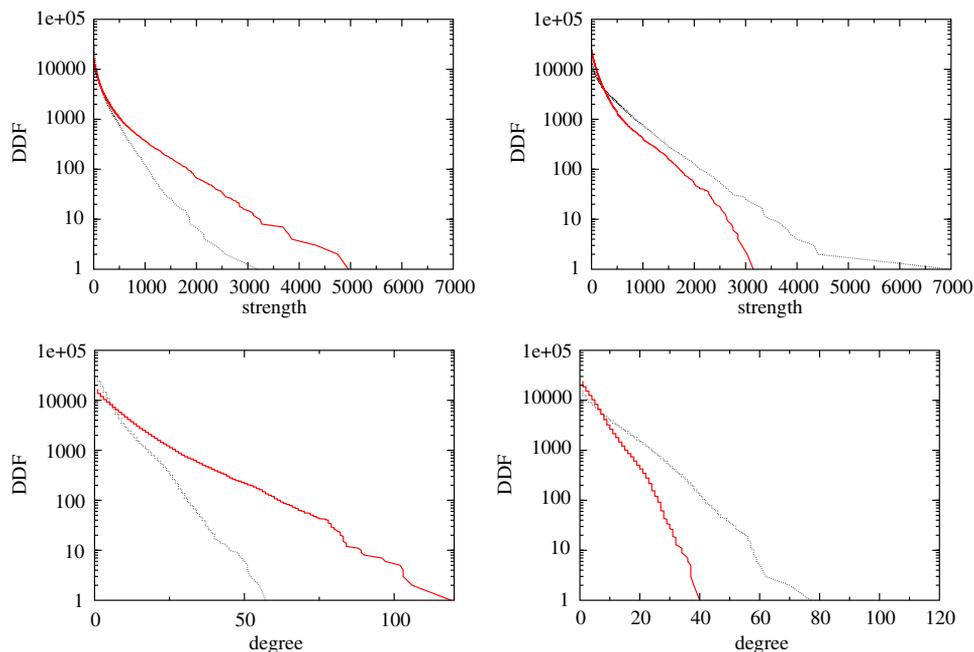


Fig. 5. Decumulative density function of strength (top) and degree (bottom) for incoming (black-dotted) and outgoing (red-solid) links in 1999 (left) and 2002 (right).

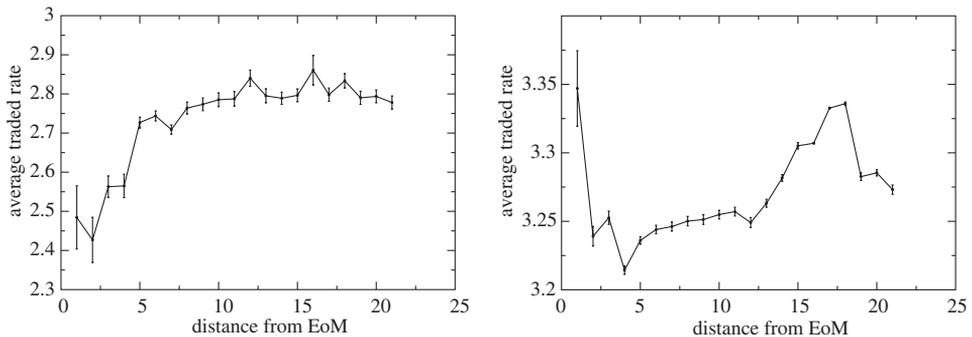


Fig. 6. Average traded interest rate in 1999 (left) and 2002 (right) as a function of the distance from the EoM.

industrialised areas had more opportunities to lend to the private sector. Consequently smaller banks may have experienced liquidity shortages that led them to act mainly as borrowers in the interbank market.

Following the introduction of the Euro, at the beginning of 2001, larger Italian banks had another channel available for liquidity management; private telephone lending to foreign banks not active on the e-MID. It is plausible that Italian banks found better profit opportunities by lending liquidity in the European market given the non-transparent, bilateral nature of these transactions. This fact together with the reduced liquidity requirements of the smaller banks, following the 2001 economic down turn, may have been responsible for the change in the trading pattern.

This change has also affected the evolution of the interbank rate over the maintenance period as shown in Fig. 6 (see also Fig. 1). While in 1999 the banking system had overall excess liquidity, with a progressive decrease of the interbank rate towards the EoM days, in 2002 the opposite situation has emerged with the system experiencing an overall shortage of liquidity and an increase of the interbank rate on EoM days.

The banking system is highly heterogeneous with a relatively small number of large banks which trade very frequently high volumes of loans and a large number of medium and small size banks that trade less frequently and in small volumes. In order to identify the differences in the liquidity management practices of banks of different sizes we split them into four groups following the Bank of Italy classification: in group 1 we have foreign banks, in group 2 there are large/medium Italian banks, in group 3 small Italian banks and in group 4 very small Italian banks.

In Fig. 7 we plot the incoming (left) and outgoing average degree (top), the maximum degree (center) and the strength (bottom) per bank in each group. The figure shows that the large Italian banks (red line) have the highest incoming degree (i.e. have the highest number of creditors), while the small Italian banks (green line) have the highest outgoing degree (i.e. have the highest number of debtors) and the foreign banks (black line) have the lowest number. Both the incoming and outgoing

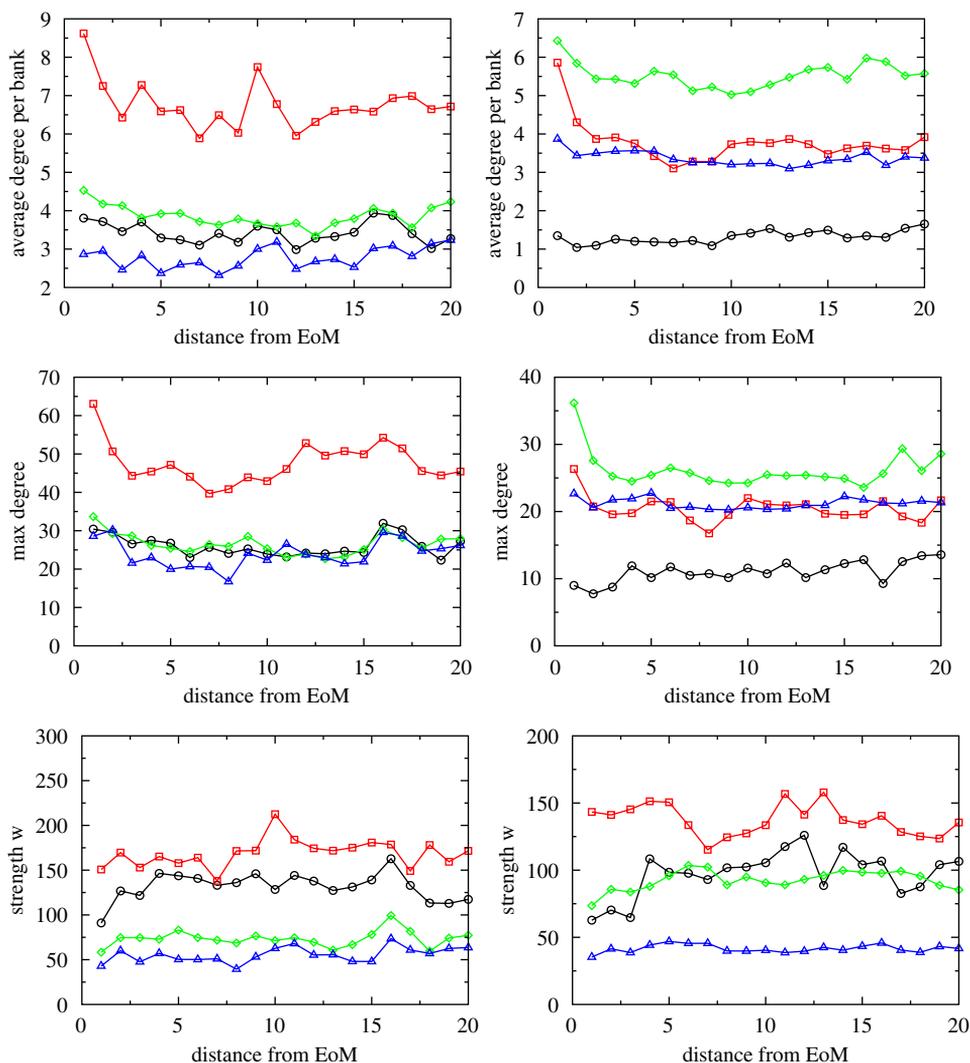


Fig. 7. Incoming (left) and outgoing (right) average degrees (top), maximum degree (centre) and strength (bottom) per bank in each group of banks: group 1 (black-circle), group 2 (red-square), group 3 (green-diamond), group 4 (blue-triangle).

degrees rise towards the EoM. As for strength, the large Italian banks are both the largest lenders and the largest borrowers followed by the foreign banks.

Fig. 8 shows the time evolution of the average flow for each group of banks. If a bank has a positive (negative) flow at the end of a given day then it has acted as an overall lender (borrower) for that day. The flow for the large banks in groups 1 and 2 is negative on average over the maintenance period while the small banks in groups 3 and 4 have an average positive flow and in effect are the overall lenders to the

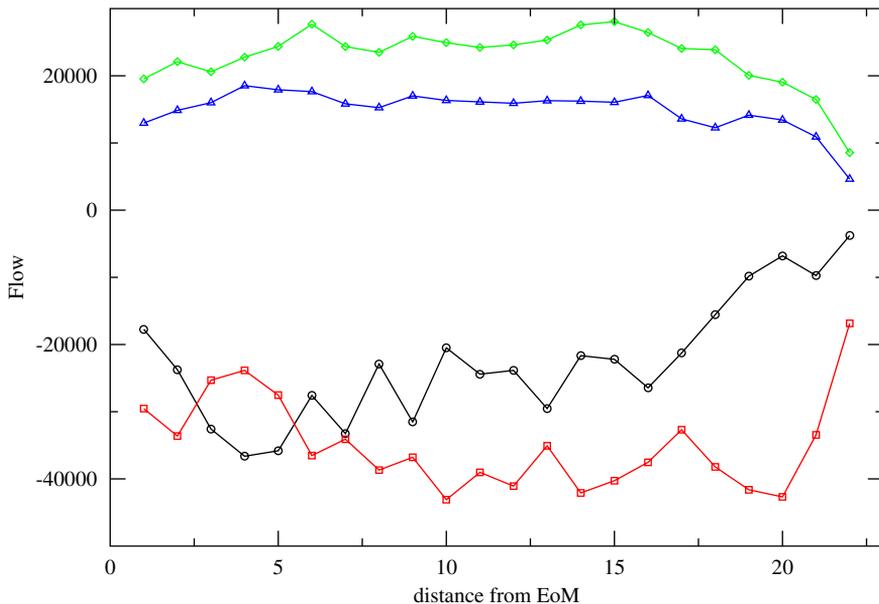


Fig. 8. Flow per group of banks in 2002 (right): group 1 (black-circle), group 2 (red-square), group 3 (green-diamond), group 4 (blue-triangle), as a function of the distance from the EoM.

banking system. This seems reasonable. Lending excess reserve in the interbank market provides an attractive, relatively low risk, profit opportunity for the small banks. Larger banks typically have better opportunities to invest their deposits more profitably in the business sector. Fig. 8 also shows that the aggregate flows for the banks in groups 1 and 2 are negatively correlated which suggests that a significant amount of trading takes place between the foreign and the large Italian banks.

Fig. 9 shows the affinity of the undirected network. The system exhibits disassortative mixing, i.e. banks with a higher degree are more likely to be connected with lower degree banks. An example of the bank network at the end of a typical day is plotted in Fig. 10. The colour code is the same as the one used in previous figures. We can clearly identify a few hubs (for example banks 123, 11, 6, and 1) connected to a large number of peripheral banks which have only a few links. Banks also tend to act as either sinks or sources, (i.e. have only incoming or only outgoing links) and only a very limited number perform both roles (i.e. banks 6, 31, 79). The direction of the arrows in Fig. 10 is from the lender to the borrower.

In Fig. 11 we show the evolution of the clustering coefficient. Given that the number of links between banks changes from day to day it is difficult to extrapolate information directly from the evolution of the clustering coefficient. Therefore, we define the relative clustering coefficient as the ratio of the clustering coefficient of the actual network to that of a random network. We construct the random network in two different ways: (a) we generate a generic random network with the same number of nodes and links as the actual network for each day and (b) we produce a random

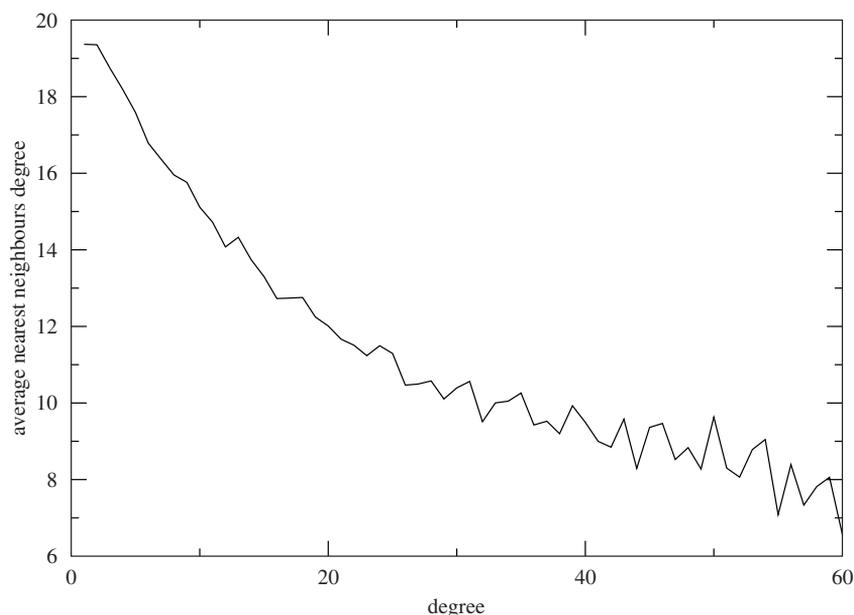


Fig. 9. Affinity in the undirected network.

network with the same number of nodes, links and the same degree distribution as the real network. We denote the two relative clustering coefficients as  $C_a$  and  $C_b$ , respectively. For the random network in case (a), the average clustering coefficient is given by  $C^r = 2N_l/N_b$ , while for the random network in case (b) an analytical formula is not available. Therefore we generated 100 random networks of type (b) for each day considered and averaged out the computed clustering coefficients. Fig. 11 (left) shows that for case (a) the relative clustering coefficient is about 1 at the beginning of the month, increases as the EoM period approaches and reaches 1.7 on the EoM day. The ratio is smaller in case (b) but follows a similar pattern. This reveals that, apart from the last few days of the maintenance period, the number of triangles in the banking network is similar or smaller than that of a random network. To have a triangle in the system at least one bank must lend to one counterparty and borrow from another. Given the transparent, multilateral nature of the market, banks do not need to act as intermediaries, which explains the low clustering. Nonetheless a bank may act as lender and borrower on the same day for different reasons; its position may change during the day as a result of unforeseen cash-flows, the bank could be trying to exploit a profit opportunity, or it may attempt to fine-tune its reserve level, which may be difficult to achieve via unidirectional operations. Further studies are required to establish the precise nature and rationale for these transactions around the EoM (see Iori et al., 2007).

Another metric we use to investigate the structural changes in the system is the network average distance, and we plot it in Fig. 12. Given that the number of banks

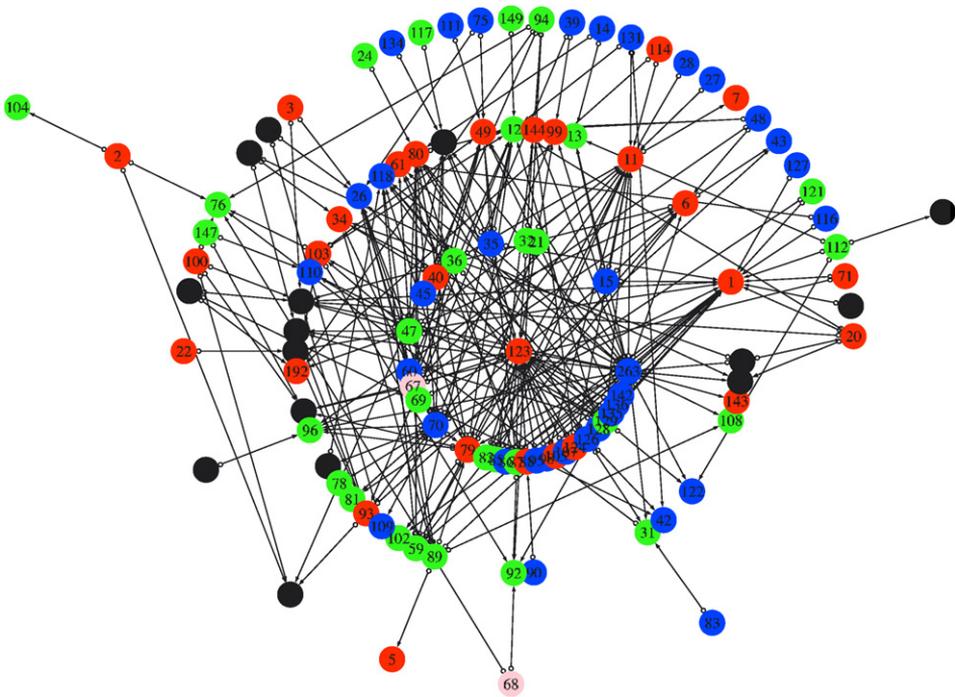


Fig. 10. Banking network on January 10, 2002: black group 1, red group 2, green group 3, blue group 4. The direction of the arrow is from the lender to the borrower, the empty circle identifies the lender bank.

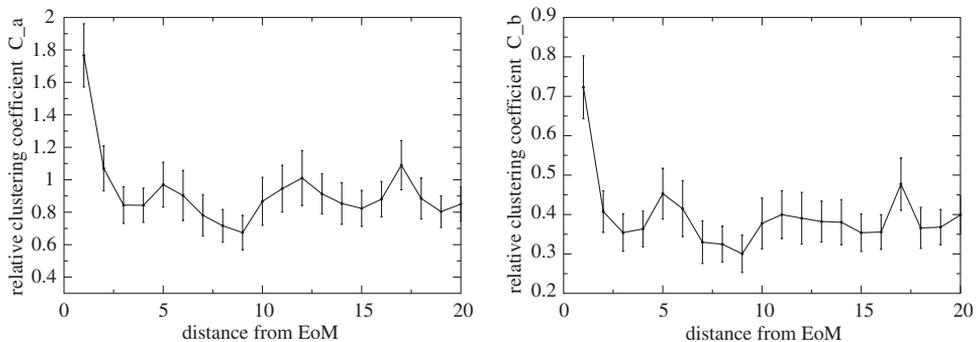


Fig. 11. Relative clustering coefficients  $C_a$  (left) and  $C_b$  (right) as a function of the distance from the EoM.

and links changes from day to day so does the average distance. Therefore we define the relative distance as the ratio of the average distance in the actual network to that in a random network constructed as in (a) and (b) above. We denote the corresponding relative distances as  $D_a$  and  $D_b$ . Both ratios are close to unity and do not change significantly over the month. This is to be expected since money does not

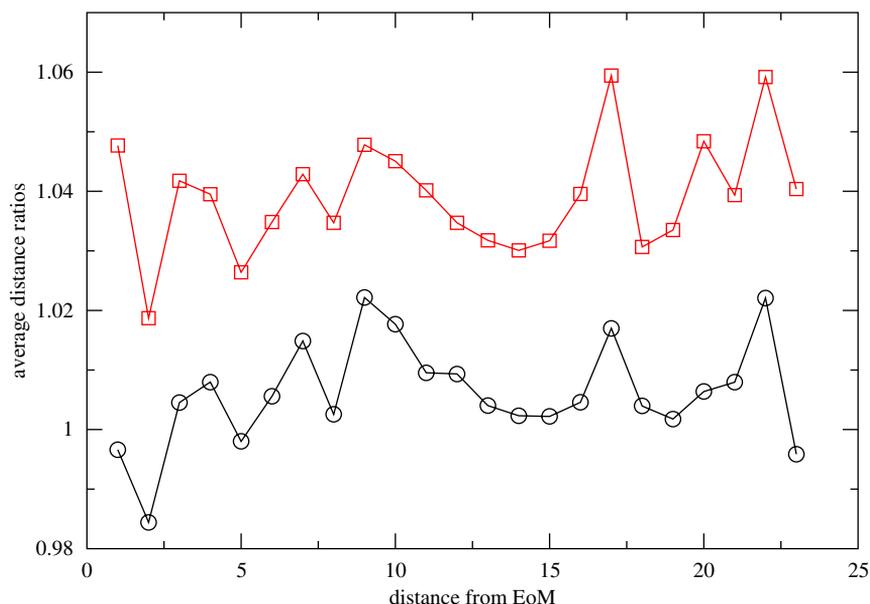


Fig. 12. Relative distances  $D_a$  (black-circle) and  $D_b$  (red-square) as a function of the distance from the EoM.

flow along long chains through the system but goes directly from the buyer to the seller without intermediaries (we have seen that banks are typically either lenders or borrowers on a given day and rarely both). Hence the topology of the network is not optimized to propagate the money flow efficiently through the system (as for example is the case in communication networks). Given that the average distance in the banking network cannot be clearly differentiated from that in a random network we can infer that this metric does not reflect the organisation of the banking network.

In Fig. 13 (left) we plot the participation ratio  $Y_2^c(i)$  as a function of a bank's inverse degree. The objective is to identify links that are used more often than others. We observe that while for a degree up to 5,  $Y_2^c(i) \sim 1/k_i$  and for higher degrees the participation ratio is slightly higher than the inverse degree indicating a slight tendency towards preferential trading. On the right side of Fig. 13 we plot the average participation ratio during the maintenance period. In both figures we separate lending (red) and borrowing (black) transactions. The participation ratio is always higher for lending transactions than borrowing transactions. This is to be expected as lenders are the ones facing credit risk. The participation ratio for lending transactions decreases around the EoM revealing that when the final liquidity adjustments cannot be further delayed the choice of counterparty becomes less important. This contrasts with the pattern observed in the Portuguese interbank market where preferential lending increases when there is a liquidity shortage.

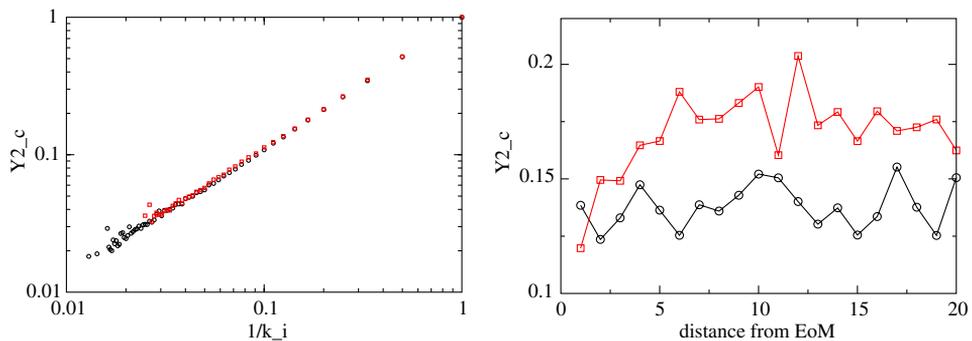


Fig. 13. (Left) Participation ratio  $Yx_2^c(t)$  as a function of  $1/k_i$  for borrowing (black-circle) and lending transactions (red-square). The continuous black line is the benchmark case of no preferential lending/borrowing. (Right)  $Y_2^c(t)$  as a function of the distance from the EoM for borrowing (black-circle) and lending (red-square) transactions.

## 6. Conclusions

We explored the network of interconnections among banks in the Italian overnight market and by applying several metrics derived from computer science and physics, uncovered a number of microstructure characteristics.

We found a clear pattern of structural change over the years and during the maintenance periods with the network degree increasing and the strength decreasing close to the EoM days. The banking network is fairly random, preferential lending is limited and money flows directly from the lender to the borrower without intermediaries. Banks do not seem to find short term profit opportunities by borrowing from some and lending to others on the same day. All of these observations suggest that the structure of the interbank market is organised relatively efficiently.

The banking system is highly heterogeneous with large banks borrowing from a high number of small creditors. Iori et al. (2006) showed in an artificial market model, that when banks are heterogeneous high connectivity increases the risk of contagion and systemic failure. The current institutional settings push banks towards an even more connected configuration as the EoM date approaches, and in doing so it may increase the potential for systemic risk. A policy implication of this work would be to encourage the design of a mechanism for reserve requirements that does not compel banks to simultaneously fulfill their average reserve. For example the single EoM date could be replaced with four monthly dates, one week apart (matching the pattern of the ECB weekly auctions). The national central banks (NCB) will have to identify an appropriate allocation mechanism so that each slot will have banks with similar liquidity needs. The settlement dates also have to be carefully chosen so that they do not coincide with periods of cash-flow constraints (such as wage or tax payments).

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