A Network Analysis of the Italian Overnight Money Market

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Abstract

The objective of this paper is to analyze, by employing methods of statistical mechanics of complex networks, the network topology of the Italian segment of the European overnight money market. We investigate differences in the activities of banks of different size and the evolution of their connectivity structure over the maintenance period. The main objectives are to understand potential implications of 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.

1 Introduction

Liquidity management in the banking system is essential for the smoothly operate of payment systems, and in particular real time gross settlement (RTGS) systems. The European Central Bank (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. Auctions were executed on a fix term rate until June 2000 and since then are 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 mondays afternoon credit institutions present their bids to the respective national central banks (NCB). Banks submit the amount of money they want to deal and interest rate they are ready to pay for it. The ECB collects bids on tuesdays morning and executes the auctions. The allocations are settled on the bank's account to the NCB on wednesdays. The Eurosystem also offers credit institutions two standing facilities: the marginal lending facility in order to obtain overnight liquidity from the central bank, against the presentation of sufficient eligible assets; and the deposit facility in order to make 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 (when this is not a holiday in which case is anticipated to the previous working day). This feature of the framework has helped to keep the volatility in overnight rates limited without the need for Eurosystem fine-tuning operations. Reserve holdings not exceeding the minimum reserve requirements are remunerated at the main refinancing rate but excess reserves are not remunerated at all. Banks can exchange reserves on the interbank market with the objective to minimize the reserve implicit costs. Credit institutions make heavy use of the flexibility provided by averaging and a typical monthly reserves pattern within the maintenance periods has emerged (Bank of England (2000)). The market normally begins each reserve maintenance period in deficit, until the ECB provides sufficient liquidity with the first MRO (main refinancing operations) of the

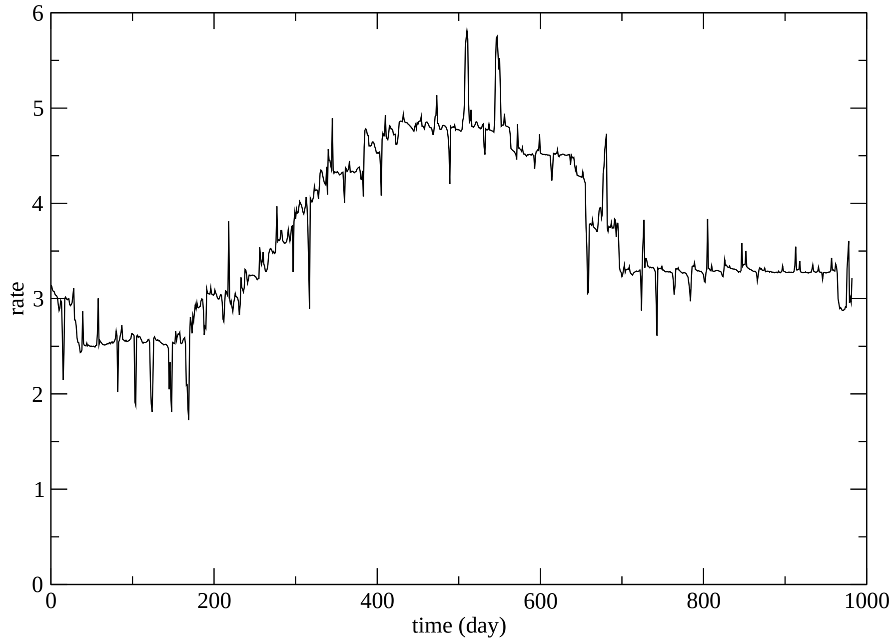

Figure 1: Time series of daily interest rate from January 1999 to December 2002.

maintenance period. There are also indications (Bank of England (2000) and Gabbi (1992)) that not all credit institutions actively manage their minimum reserves. Some, particularly smaller, institutions tend to keep their reserve account at the requisite level constantly through the maintenance period, although some might use the relevant amounts intraday to meet their need for payment system liquidity.

The stabilizing effect of the averaging provision 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-December 2002 displayed in Figure 1. On or shortly before the 23rd of each month overnight rates either exhibit a sharp deep (excess liquidity compared to the required minimum reserve average) or a sharp peak (shortage of liquidity). The overnight rate is bounded above and below by the official rates corridor fixed by the ECB: banks may borrow against collateral at the rate on the marginal lending facility (the ceiling) or deposit funds at the rate on the overnight deposit facility (the floor). Usually the overnight rate pattern is above the main refinancing rate since the banking system is liquidity short, so to make effective the monetary policy managed by the central bank. The highest draw-down of the euro overnight interest average (EONIA) has been experienced for the Twin Towers attack (time day 660) when both FED and ECB decided to cut official interest rates of 50 basis points giving, at the same time, a large amount of liquidity to support market prices. From November 2001 (time day 700) to the third quarter of 2002 the main refinancing rate does not change from the level of 3,25 per cent. Consequently the interest rate volatility declines, with slight changes coherent with the monthly maintenance periods still visible.

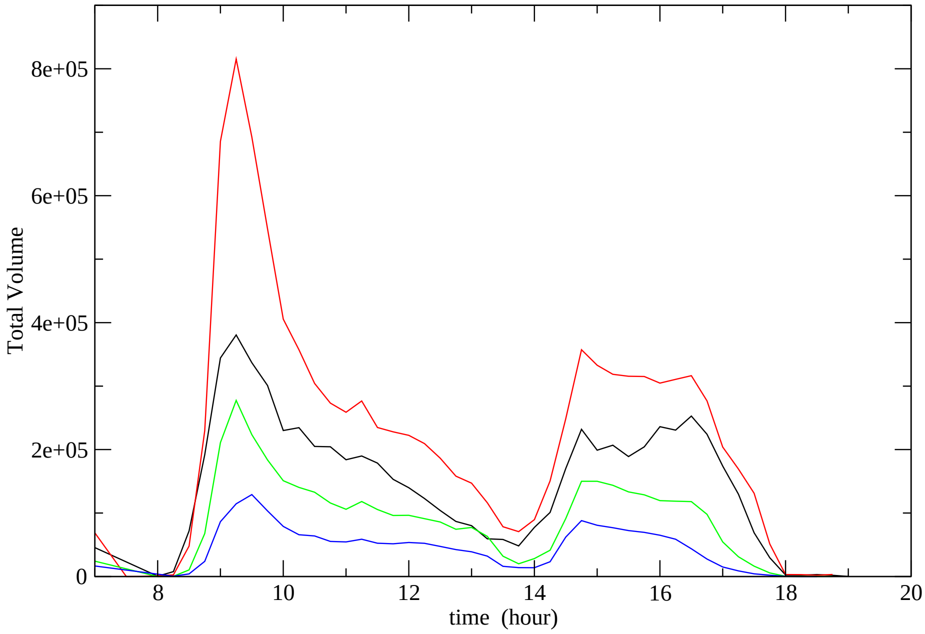

Figure 2: Average intraday pattern per group of bank, over the period 1999-2002; black group 1, red group 2, green group 3, blue group 4

A few papers have been investigating intraday and intra-mantenance-period patters in the European money market. Evidence has been reported of a typical intraday pattern for the number of contracts (Hartmann et al. (2001), Barucci et al. (2004)) which follows a bimodal profile, with the first peakq in the middle hours of the morning higher than the one in the afternoon. This pattern is shown in figure 2 for different categories of banks[1]. The events that contribute to the above intra-day patterns have been identified as follows: around 9:00 am pending payments of various nature are settled automatically, the bulk of which consists of previous day e-MID contracts; around 12:00 am banks settle the balance of net payment systems BI-COMP; around 12:30 pm banks settle the cash leg of the net security settlement systems; in the afternoon banks mainly settle financial and interbank payments.

As for 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. Also they have reported a short period of high market activity without particularly large spreads after the auction suggesting 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 number of contracts on the last few days of the maintenance periods. This pattern is shown in figure 3: we plot in red the amount borrowed (left) and the number of transactions (right) per borrowing bank and in black the corresponding amounts per lending bank.

[1]The classification of banks in groups is given in the Appendix and explained in section 4.

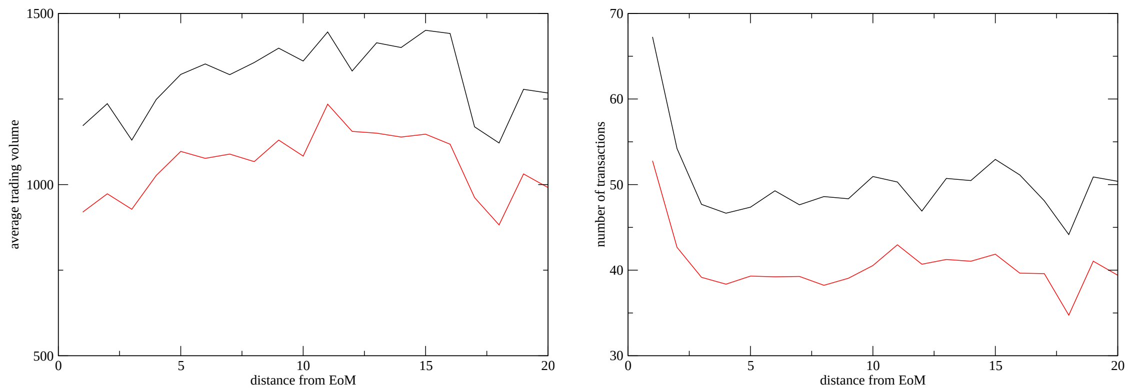

Figure 3: Average daily trading volume (left) and daily number of transactions (right) over the period 1999-2002.

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.

The nature of credit and debit relationships among banks has been shown to be a crucial ingredient for the emergence of contagion and systemic risk in the interbank market and in payment systems (Angelini (2002), Furfine (2003) Iori and Jaffrey (2003), Iori at al. (2004)). Furthermore, recent studies on general complex networks (Internet, World Wide Web, collaboration networks, biological networks, communication networks, power networks etc) have shown that the topology of a network affects its functionality and stability (Albert and Barabasi (2002), Newmann (2004)). Scale-free networks (i.e. networks with a power low 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, simultaneity of an attack on hubs is important as scale-free networks can heal themselves rapidly if an insufficient number of hubs necessary for a systemic collapse are removed. Scale-free networks are also extremely vulnerable to epidemics (Barthelemy 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. Economic theory is also starting to acknowledge the importance of network topology. The role of the scale-free networks has been intensively studied in the formation of economic and financial structure for example in the case of board of directors (Battiston et al. (2003)), the case of stock ownership networks (Garlaschelli et al. (2005)) and the case of stock price correlations networks (Bonanno et al. (2003)). Nonetheless not much attention has yet been devoted to the empirical study of the topological properties of the banking network, with the exception of the paper by Boss et al (2003) which analyzes the network of overall credit relationships in the Austrian Interbank market. In their study the authors analyze all the liabilities for ten quarterly single months periods, between 2000 and 2003, among 900 banks. They found 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 with each other).

Our paper focuses on the network analysis of the overnight maturity on the e-MID interbank market. 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 with whom to trade, the information about the rates and the trades are public. We investigate differences in the activities of banks of different size and the evolution of their connectivity structure over the years and over the maintenance period. The main objectives are to understand potential implications of the current institutional arrangement on the stability of the banking system and second to assess the efficiency of the interbank market.

Section 2 describe the database. Section 3 explains how we construct alternative banking networks and discuss the measures we use to analyze them. Section 4 discuss the results and section 5 concludes.

2 e-MID and Dataset

The Italian electronic broker market MID (Market for Interbank Deposits)[2] covers the entire existing domestic overnight deposit market in Italy. Both Italian banks and foreign banks can exchange funds on the e-MID. The 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 TARGET). Trades are in euros and USD for maturities between overnight and one year; 90% of the trades are overnight. Rates can be expressed in basis points or 1/16ths for the Euro and in basis points or 1/32nds for the US Dollar. The minimum quote is 1.5 million Euros and 5 Million US dollars. Each quote is identified as an offer or a bid. An offer indicates that the transaction has been concluded at the selling price of the quoting bank while a bid indicates that a transaction has been concluded at the buying price of the quoting bank. The names of the banks are visible next to their quotes to facilitate credit line checking. Quotes can be submitted and a transaction is finalized if the ordering bank accepts a listed bid/offer. When a bid rate is hit, the transaction can be executed automatically or manually within 90 seconds, if a bank prefers to first check the lending counterpartys name. Whilst in the case of a hit on an offer rate, this always needs to be accepted manually within 90 seconds, to allow for credit line checking. The market also permits bilateral trades with a specific counterpart of choice[3].

[2]e-MID is run by e-MID S.p.A. Società Interbancaria per l'Automazione (SIA), Milan. The central system is located in the office of the SIA and the peripherals on the premises of the member participants.

[3]For more details see http://www.e-mid.it/index.php/article/articleview/85/0/29/.

Our data set consists of all the overnight transactions concluded on the e-MIB from January 1999 to December 2002 for a total of 586,007 transactions. 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 bank. The information about the parties involved in a transaction allows us to perform an accurate daily analysis of the connectivity among banks and it's change over time.

3 Network Analysis

Given our dataset, we can define three daily matrices: the adjacency matrix A, the connectivity matrix C and the weighted connectivity matrix W. The element of the adjacency matrix a_{ij} indicate if a transaction between bank i and bank j has occurred during a given day, i.e. $a_{ij} = 0$ if no transaction has occurred and $a_{ij} = 1$ if at least one transaction has occurred. The elements of the connectivity matrix c_{ij} denote the number of transactions between bank i and bank j in a given day. The elements of the weighted connectivity matrix w_{ij} denote the overall volume exchanged between bank i and bank j in a given day. The number of active links in the network is defined as $N_l = \sum_{ij} a_{ij}/2$, the number of transactions as $N_T = \sum_{ij} c_{ij}/2$ and the overall trading volume as $V = \sum_{ij} w_{ij}/2$. 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 dataset also allow us to construct matrices associated to directed graphs. We can make links directional by allowing them to follow the flow of money, so that a link is incoming to the buyer and outgoing from the seller. A directed graph may be more relevant if one was 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^b_{ij} (a^l_{ij}) indicate if at least one transaction has occurred on a given day between bank i and bank j with bank i as the borrowing (lending) bank. The elements of the connectivity matrix c^b_{ij} (c^l_{ij}) denote the number of transactions on a given day between bank i and bank j with bank i as the borrowing (lending) bank. The elements of the weighted connectivity matrix w^b_{ij} (w^l_{ij}) denote the overall volume exchanged on a given day between bank i and bank j with bank i as the borrowing (lending) bank. Obviously $w^l_{ij} = w^b_{ji}$. We define the flow between two banks as $f_{ij} = w^l_{ij} - w^b_{ij}$. 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. Recently the focus has shifted to weighted networks. A set of metrics combining weighted and topological observables have been proposed to characterize the statistical properties of the strength of edges and vertices and to investigate the correlations among weighted quantities and the underlying topological structure (Barrat et al. (2004), Newman (2004), Dorogovtsev and Mendes (2003)). Among the commonly used metrics are:

- *Degree*

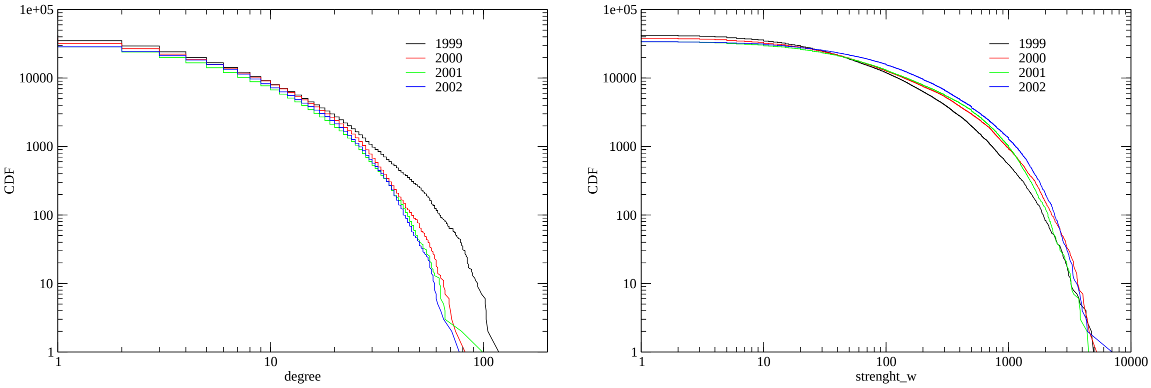

Figure 4: Cumulative distribution of banks degree (left) and strength (right) for each year during 1999-2002.

The degree of a node is defined as

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

where the sum runs over the set $\mathcal{V}(i)$ of neighbors of i. The in-degree k^b and out-degree k^l are defined as

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

Random networks (i.e. networks where the N nodes are connected at random with a given probability ϕ) are characterized 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-low $p(k) \sim k^{-\gamma}$. In the last case the network is called scale-free.

- *Strenght*

  Another measure of the network properties in terms of the actual weight of each link (i.e. the size of the trade on that link, or the number of times the link has been used) is obtained by looking at the vertex *strength*.

  We define the vertex strength s_i^w as

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

  and the vertex strength s_i^c as

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

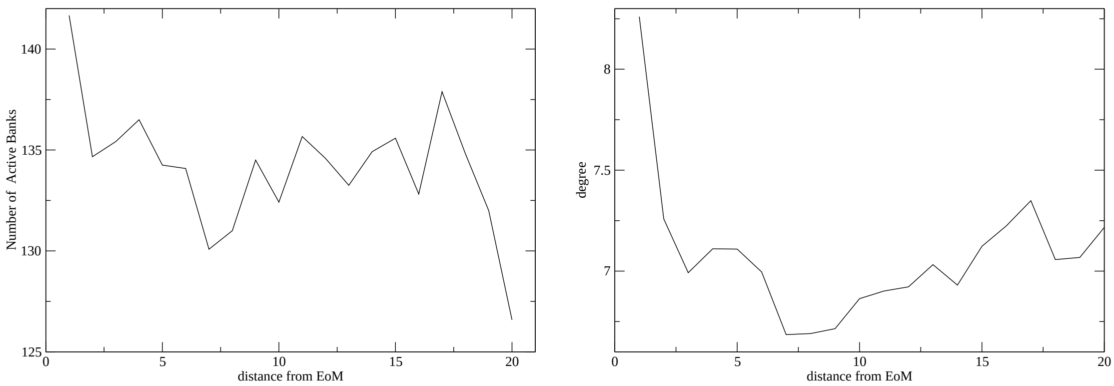

Figure 5: Average number of active banks (left) and average degree (rigth) in 2002.

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

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

Similarly we can define the borrowing and lending strength as

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

and the equivalent expressions for $s_i^{c,b}$ and $s_i^{c,l}$.

- *Affinity*

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

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

  If $k_{nn}(k)$ is an increasing function of k vertices with high degree have a larger probability to be connected with large degree vertices. This property is called *assortative mixing*. A decreasing behavior of $k_{nn}(k)$ with k defines *disassortative mixing*, in the sense that high degree vertices have a majority of neighbors with low degree, while the opposite holds for low degree vertices.

- *Clustering*

  The clustering coefficient c_i is a measure of the density of connections around a vertex and is defined as

$$c_i = \frac{2}{k_i(k_i-1)} \sum_{j,h} a_{ij} a_{ih} a_{jh}. \tag{8}$$

  Hence, the clustering coefficient allows to calculate the proportions of nearest neighbors of a node that are linked to each others (in our contest, if there exist a link between two banks who have a common trading partner bank). The average clustering coefficient,

$$C = \frac{1}{N} \sum_i c_i$$

expresses the statistical level of cohesiveness measuring the global density of interconnected vertex triplets in the network.

- *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 distances. If the graph is not connected, the average distance is defined as the average among all distances for pairs both belonging to the same connected component. The diameter of a graph is given by the maximum of all distances between pairs.

- *Participation ratio*

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

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

  or equivalently

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

  If all weights are of the same order then $Y_2 \sim 1/k_i$ while if a small number of weights dominate Y_2 is close to 1. A value of the participation ratio close to one would then indicates preferential relationships among banks[4].

  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

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

4 Results

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

[4]Note that the statistics used by Cocco et al. (2003) is the lender preference index (LPI) (and the corresponding borrower preference index) defined as $LPI = \frac{\sum_{t=1}^{30} w_{i,j}^l(t)}{\sum_{t=1}^{30} s_i^{w,l}(t)}$

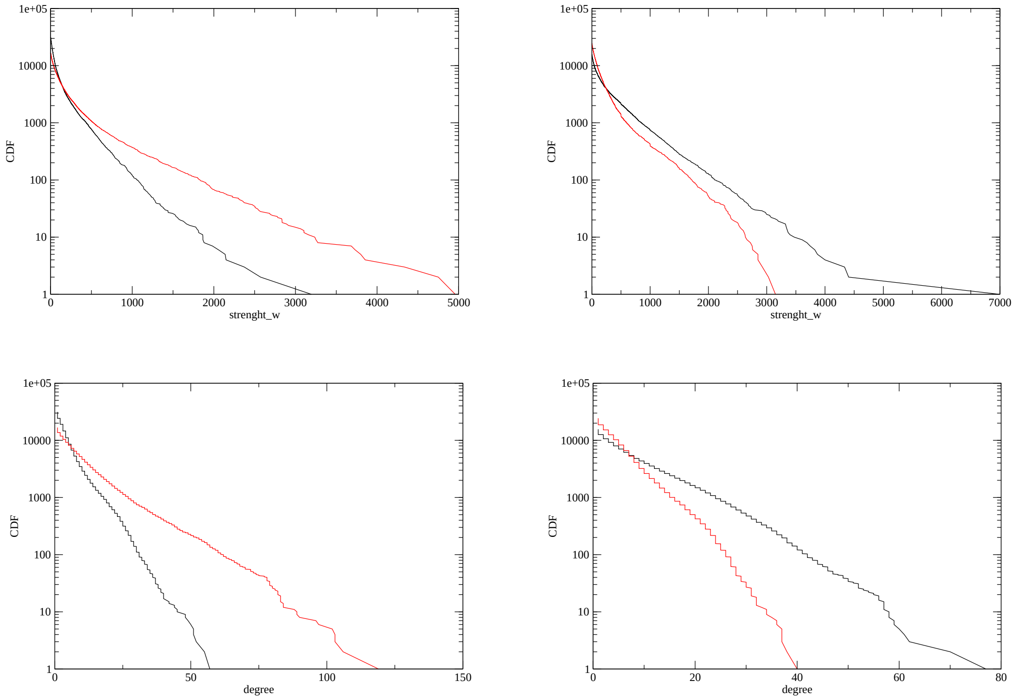

Figure 6: Cumulative distribution of strenght (top) and degree (bottom) for incoming (black) and outgoing (red) links in 1999 (left) and 2002 (right).

In figure 4 we show that the banking system is highly heterogeneous with both the daily cumulative distribution of banks' degrees (number of counterparts) and strengths (trading volumes) fat tailed.

In figure 5 we plot the average daily 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 than not only the number of transaction increases toward the EoM, as previously shown in figure 3, but also the number of active links and the number of trading bank. This suggests that final adjustments to liquidity are achieved through a larger number of smaller volume trades, involving a larger than usual number of counterparts. Barucci et al. (2004)) interpreted these observations as a sign that banks manage their liquidity efficiently so that on the EoM days only small adjustment are necessary to the average reserve. Nonetheless, the increase of trading banks and trading partners on the EoM days, is also compatible with a less optimistic picture: banks have less liquidity available to offer on the market on EoM days so that borrowing banks need to engage in a higher number of transactions with several counterparts to collect, wherever is still available, the liquidity they need to balance their reserves.

In figure 6 we compare the cumulative distribution of banks' degree and strength for the entire system in 1999 and 2002. The figure provides clear evidence that the market has undergone a transition over time moving from a situation in 1999 where 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 trade with a larger number of counterparts when buying liquidity and a smaller number

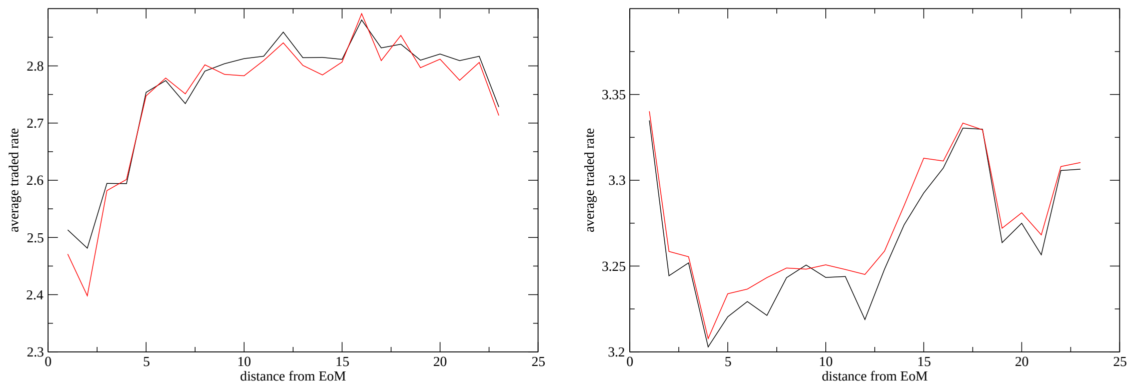

Figure 7: Average traded rate in 1999 and 2002 as a function of the distance from the EoM.

of counterparts when selling it. This change can be understood by analyzing the behaviour of the interbank rate in figure 7 (see also figure 1). While in 1999 the banking system experienced excess liquidity, with a progressive decrease in the interbank rate close to the EoM days, in 2002 the opposite situation has emerged with the system experiencing a shortage of liquidity and an increase of the interbank rate on EoM days (the black line is the average rate payed by borrowing banks and the red line the average rate received by lending banks). The plots in figure 6 are on a linear-log scale while those in figure 4 are on a log-log scale. The distributions seem to be somewhere in between power-low and exponential. The maximum degree is lower in 2002 both for incoming and outgoing links as a consequence of the high number of mergers among banks which has reduced the number of those participating in the e-Mid from 215 in 1999 to 177 in 2002.

In order to identify differences in the liquidity management behaviour of banks of different sizes we split them in four groups following the classification of the Bank of Italy (see Appendix): in group 1 we have foreign banks, in group two large/medium Italian banks, in group 3 small Italian banks and in group 4 very small Italian banks.

In figure 8 we plot the incoming (left) and outgoing average degree (top), the maximum degree (center) and the strenght (bottom) per bank in each group. The figure shows that the large Italian banks (red lines) are the ones with the highest incoming degree (i.e. the ones with the highest number of creditors), while the small Italian banks (green line) are the ones with the highest outgoing degree (i.e. the ones with the highest number of debtors) and the foreign banks (black line) the ones with the lowest. Both the incoming and outgoing degrees increase toward the EoM. As for the strength, the large Italian banks are both the largest lenders and largest borrowers followed by the foreigners banks. Figure 9 shows the time evolution of the average flow per group of banks. If a bank has a positive (negative) flow at the end of a given day it has acted as an overall lenders (borrowers) for that day. The flow for the large banks in group 1 and 2 is negative on average during the all maintenance period while the small banks in group 3 and 4 have an average positive flows and act as the overall lenders to the banking system. This seems reasonable. Lending excess reserve in the interbank market

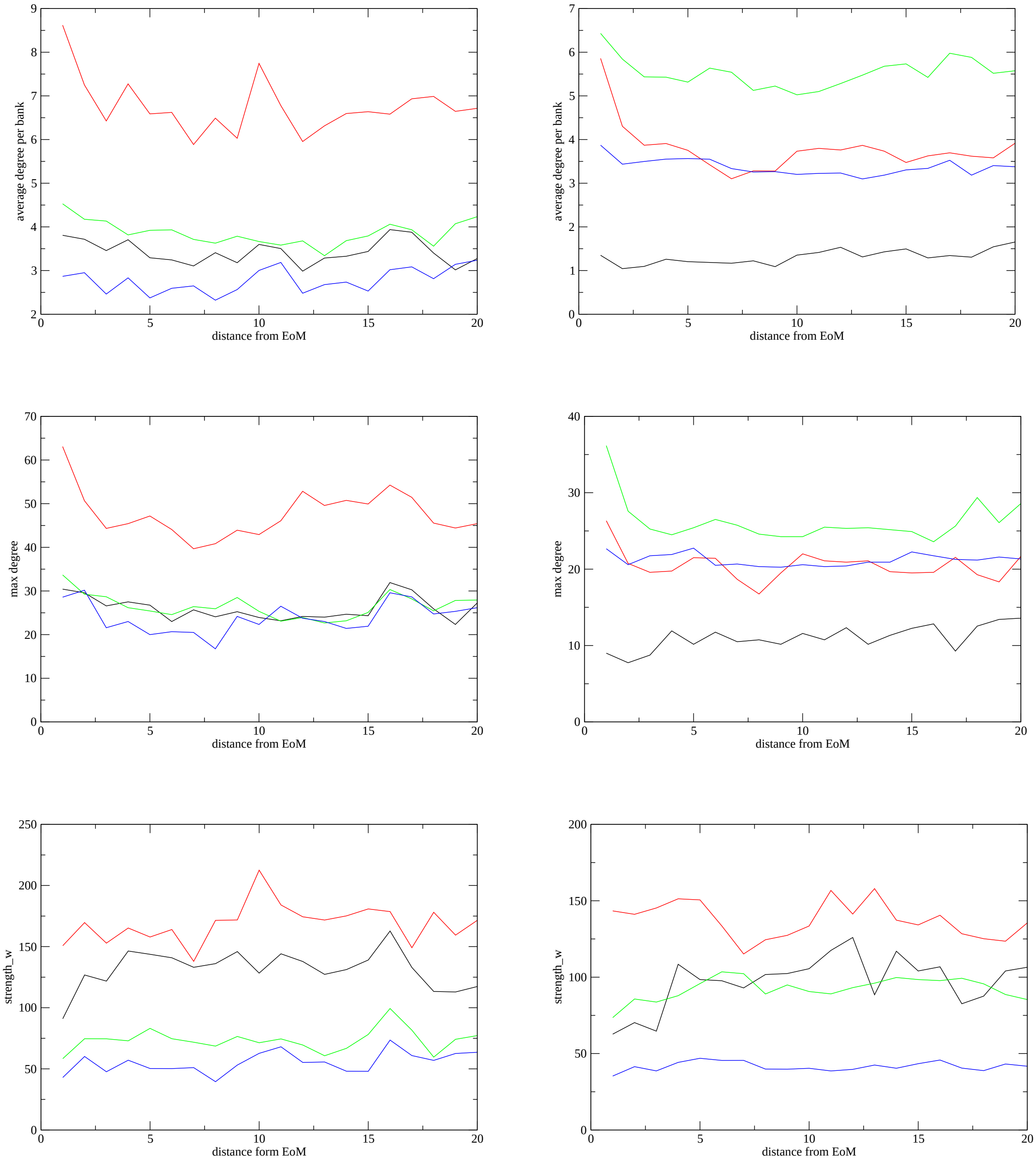

Figure 8: Incoming (left) and outgoing average degree (top), maximum degree (center) and strenght (bottom) per bank in each group of banks: black group 1, red group 2, green group 3, blue group 4.

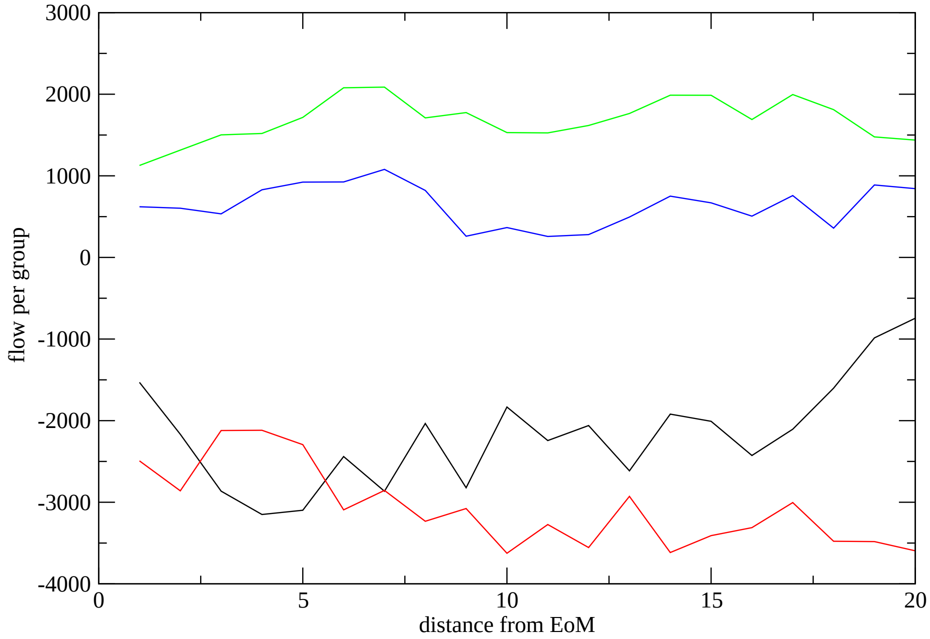

Figure 9: Flow per group of banks: black group 1, red group 2, green group 3, blue group 4, as a function of the distance from the EoM.

provides an attractive, relatively low risk, profit opportunity to the small banks. Larger banks nonetheless typically have the opportunity to invest more profitably their deposits into the business sector. Figure 9 also shows that the flows of banks in group 1 and 2 are anti-correlated revealing that a large volume of trading undergoes between foreign banks and the large Italian banks.

In figure 10 we study the affinity of the undirected network. The system shows disassortative mixing, i.e. banks with higher degree are more likely connected to banks with lower degree. The network at the end of a typical day is plotted in figure 11. The color code is the same as the one used in the previous figures. We can clearly identify a few hubs (like banks 123, 11, 6, and 1) connected to a large number of peripheral banks which have only a few links. Also banks typically are either sinks or sources, i.e. have only incoming or only outgoing links, and only a very few banks (like banks 6, 31, 79) have both (the direction of the arrow is from the lender to the borrower; the empty circle identify the lender bank).

In figure 12 we study the clustering coefficient. Given that the number of banks and number of links change from day to day is difficult to extrapolate information directly from the evolution of the clustering coefficient. Hence, 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 take a generic random network with the same number of nodes and links as the actual network for each day (b) we take a random network with the same number of nodes and links and also the same distribution of degrees. We denote the two relative clustering coefficient respectively as C_a and C_b. For the random network of case (a) the average clustering

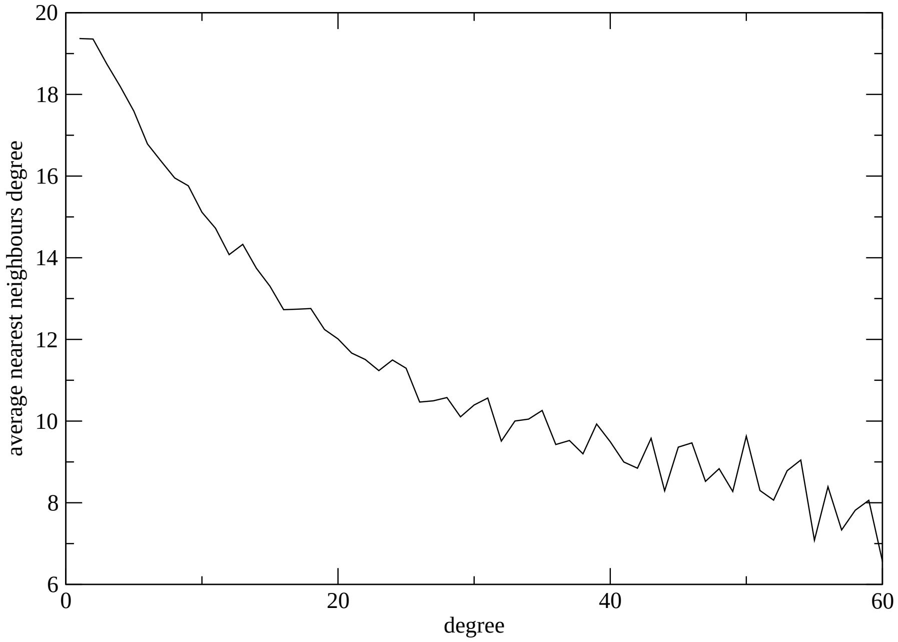

Figure 10: Affinity in the undirected network.

coefficient is given by $C^r = \frac{2N_l}{N_b}$ while for the random network of case (b) an analytical formula is not available. We have hence generated 100 random networks of type (b) for each day considered, calculated the clustering coefficients for each of them and then averaged it. Figure 12 (right) shows that for case (a) the relative clustering coefficient is about 1 at the beginning of the month, increases as we reach the EOM period and raises to about 1.7 on the EoM. The ratio is smaller in case (b) but follows a similar pattern. This reveals that, a part from the last few days of the maintenance period, the number of triangles in the banking network is comparable or smaller to that of a random network. To have a triangle in the system at least one bank must lend from one counterpart and borrow to 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 because of unforeseen cash-flows, the bank may be trying to exploit a profit opportunity, or the bank may be trying to fine tune its reserve level, which may be difficult to achieve via one way transactions. Further study in needed to clarify which of these activities banks may be undertaking (see Reno' et al. (2005)).

As a last metric to investigate structural changes of the network we measure the network average distance, and plot it in figure 13. Given that the number of banks and number of links change from day to day so does the average distance. Hence we calculate the relative distance defined 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 one and do not change significatively with the time of the month. This could have been expected since money does not flow through the system along long chains (we have seen that banks are

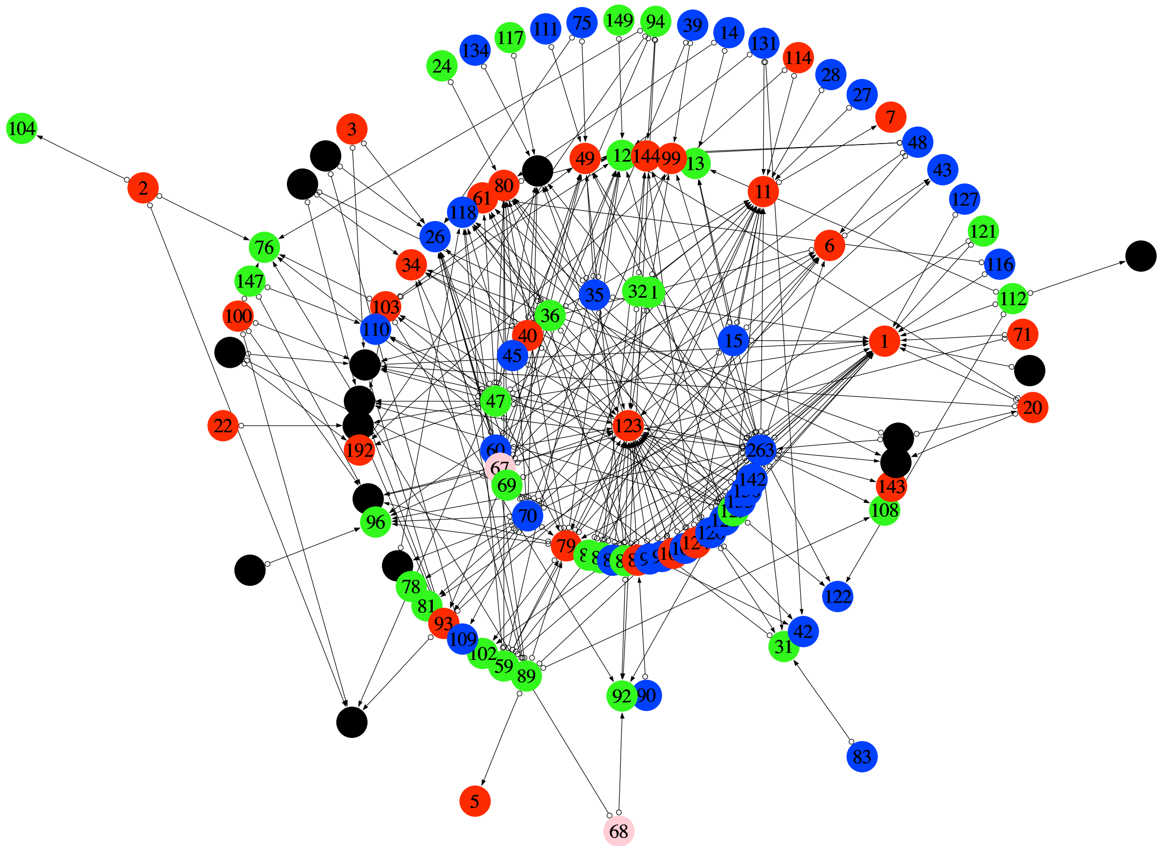

Figure 11: Banking network on January 10, 2002: black group 1, red group 2, green group 3, blue group 4. The direction of the arrow is from the lender to the borrower, the empty circle identify the lender bank.

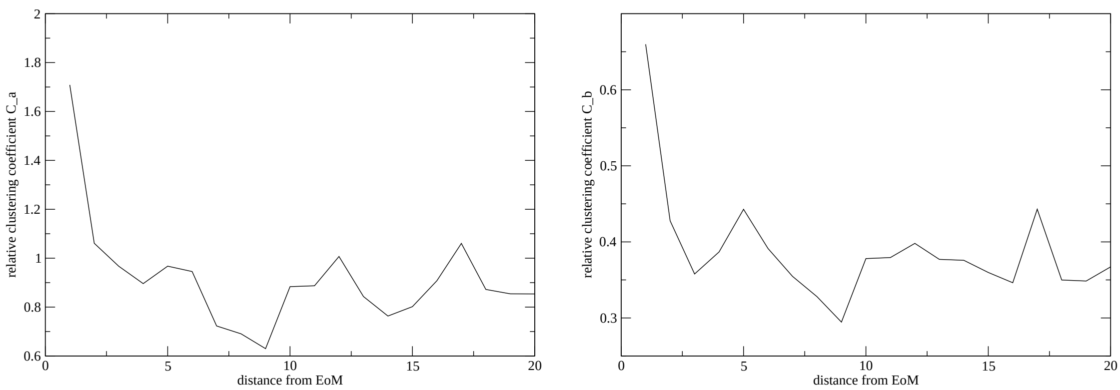

Figure 12: Relative clustering coefficient C_a (left); Relative clustering coefficient C_b (rigth) as a function of the distance from the EoM.

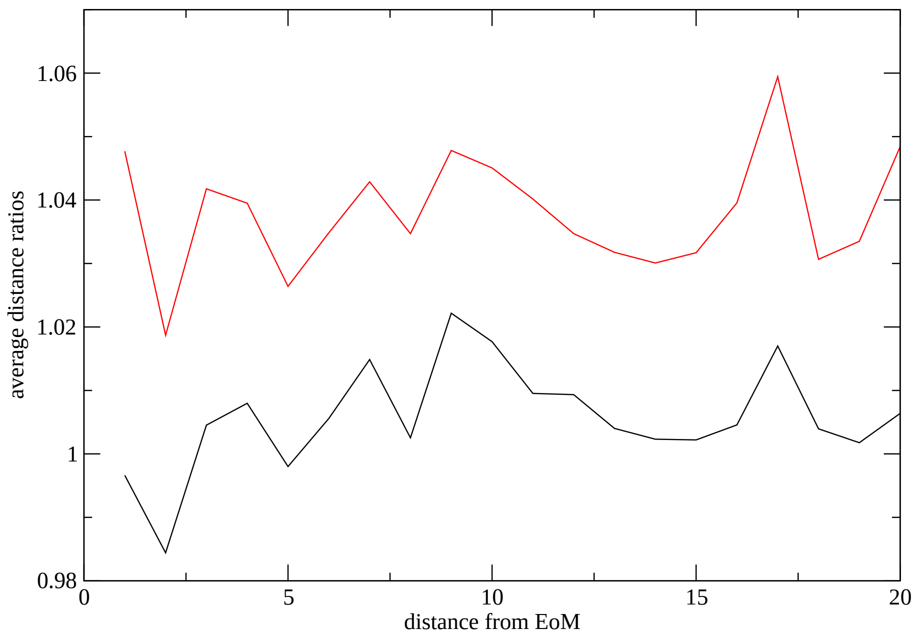

Figure 13: Relative distance D_a (black) and relative distance D_b (red) as a function of the distance from the EoM.

typically either lender or borrowers on a given day and rarely both). Hence the average distance is not associated to the functionality of the banking network and so forth it does not change over time and does not deviate from that of a purely random network.

In figure 14 (left) we plot the participation ratio $Y_2^c(i)$ as a function of the 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 five $Y_2^c(i) \sim 1/k_i$, for higher degree the participation ratio is slightly higher than the inverse degree revealing a small tendency towards preferential trading. On the right side of figure 14 we plot the average participation 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 final adjustment to the liquidity cannot be further delayed the choice of the counterpart becomes a less important matter. This contrast the pattern observed in Portugal where preferential lending increases when the market is liquidity short.

5 Conclusions

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

We found a clear patterns of structural change over the years and during the maintenance

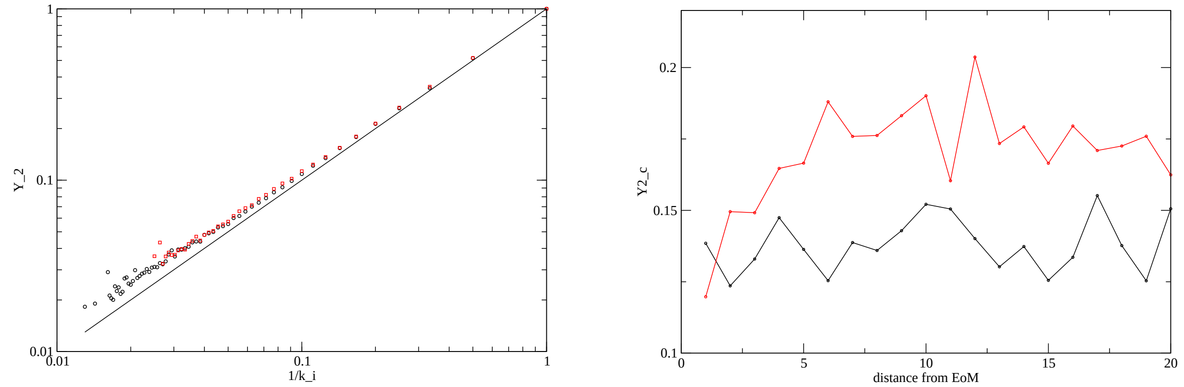

Figure 14: (Left) Participation ratio $Y_2^c(i)$ as a function of $1/k_i$ for borrowing (black) and lending transactions(red). The continuous black line is the benchmark case of no preferential lending/borrowing. (Right) $Y_2^c(t)$ as a function of the distance from the EoM for borrowing (black) and lending (red) transactions.

period 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 cash flows directly from the lender to the borrower without intermediaries. Banks also do not seem able to exploit short term profit opportunities by borrowing from some and lending to others on the same day. All these observations suggest that the interbank market is relatively efficient.

The banking system is highly heterogeneous and is arranged in a configuration with large banks borrowing from a large number of small creditors. Iori et al. (2004) showed, in artificial market models, that when banks are heterogeneous a high connectivity increases the risk of contagion and systemic failure. The current institutional settings push banks towards a even more connected configuration as the EoM date approaches, and doing it may increase the potentials for systemic risk. A policy implication of this work could be to encourage the design of a mechanism for reserve requirements that does not require banks to simultaneously fulfill their average reserve.

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Appendix

We report below the classification of banks per group.

Group1

Barclays Bank, Credit Suisse (Italy) Spa, Banque Gnerale Du Luxembourg, Credit Agricole S.A., Dresdner Bank Ag, Barclays Bank London, Rabobank International, Salomon Brothers Ag, Bank Of America N.A. - London, Banque San Paolo France, Credit Commercial De France, Bayerische Landesbank Girozent, Maple Bank Gmbh, Hsbc Trinkaus & Burkhardt, Deutsche Bank Spa, Bnp Paribas - Succ. Milano, Credit Agricol Indosuez - Milano, Banco Do Brasil S.A., Ing Bank, Citco Bank Nederland N.V., The Bank of Tokio - Mitsubishi, Arab Banking Corporation, Citibank N. A., B.Co Bilbao Vizcaya Arg.-Milan, Rasbank Spa, Ubae Arab Italian Bank.

Group2

B. Pop. Di Milano, Banca Nazionale Del Lavoro, Dexia Crediop Spa, B. Pop. Di Novara Spa, B. Pop. Di Sondrio, Banca Popolare Di Vicenza, Credito Emiliano, Banca Delle Marche Spa, Banca Carige, Mediobanca, Banco Di Napoli, Intesabci S.P.A, Imi Banca D'interm. Mobiliare, Banco Di Sardegna Spa, Unicredito Italiano, Banco Di Sicilia Spa, Credito Bergamasco, San Paolo Imi S.P.A., Banca Toscana, Banca Monte Paschi Siena Spa, Rolo Banca 1473 Spa, Abaxbank S.P.A., Banca Antoniana - Pop. Veneta, B. Pop. Comm. E Indust., Banco P. Verona E Novara Scrl, B. Pop. Di Bergamo, Centrobanca, C. R. Firenze Spa, B. Pop. Dell'emilia Romagna, B. Pop. Di Lodi, Mps Merchant S.P.A.,

Group3

Banca Di Piacenza S.C.R.L., Banca Fideuram, Banca Akros, Credito Valtellinese, Banca Eurosistemi Spa, C. R. Bolzano, C. R. Chieti, C. R. Prov. Di Teramo, Banca C.R. Asti, Banca Intermob.Invest. Gest., C. R. Di Padova E Rovigo, C. R. Di San Miniato, Banca Monte Parma, Irfis-Mediocred. Della Sicilia, Interbanca, Banca Mediolanum, Banca Generali Spa, Banca Del Salento, Banca Del Fucino, Unipol Banca, Banca Agricola Mantovana, Banca Popolare Di Spoleto, B. Pop. Di Bari, B. Pop. Di Brescia, B. Pop. Di Cremona, B. Pop. Di Puglia E Basilicata, B. Pop. Dell'etruria E Lazio, B. Di Cred. Pop. Siracusa, B. Cred. Pop.Torre Del Greco, B. Pop. Di Ancona, Banca Di Sassari, C. R. Fermo, Banca Sella, Cassa Lombarda, B. Pop. Pugliese.

Group4

C. R. Di Biella E Vercelli, C. R. Alessandria, C. R. Di Rimini Spa-Carim, Banca Legnano, C.Sovv. Risp. Pers.B. D'italia, B. Pop. Dell'alto Adige, B.C.C. Di Roma, B.C.C. Di Cambiano E Castelf., Banco Di Desio E Della Brianza, C. R. Cento, C. R. La Spezia Spa, Banca Passadore & C., C. R. Fabriano E Cupramontana, C. R. Ferrara, Cassa Risp. Pescara Loreto Apr, C. R. Di Ravenna, C. R. Torino Spa , C. R. Di Volterra, Banca Del Piemonte, Banca Di Bologna, Meliorbanca Spa, Credito Fondiario Industriale, Mcc S.P.A., Banca Arditi Galati, Banca Lombarda, Findomestic Banca Spa, Unibanca Spa, Banca Reale, Banca Federico Del Vecchio, B.Co Chiavari E Riviera Ligure, Banca Apulia, C. Cen. Raiffeisen Alto Adige, Banca Di Imola S.P.A., Veneto Banca, Banca Di

Cividale Spa, C. Dei Risparmi Di Forli', Cariprato C.R. Prato, C.R.A. Di Cantu' B.C.C, B. Cred. Coop. Carate Brianza, Banca Di Cred.Coop.Di Carugate, C.R.A. Di Manzano, Mediocred. Trentino Alto Adige, Banca Del Gottardo, B. Agr. Pop. Di Ragusa, B.Ca Coop. Catt. Montefiascone, B. Pop. Del Lazio, B. Pop. Del Trentino S.P.A., B. Pop. Di Fondi, B. Pop. Cassinate, B. Pop. Di Intra, B. Pop. Di Marostica.

Group5

Iccrea Spa, C. Centr. Casse Rur. Trentine, Ist. Centrale Banche Popolare.