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Structure in the Italian Overnight Loan Market

by

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Abstract:

We analyze the Italian interbank loan market from 1999 until 2010. The analysis of net trade flows shows a high imbalance caused by few large net borrowers in the market. The trading volume shows a significant drop starting in 2007, which accelerates with the Lehman default in late 2008. The network, based on trading relationships, is very dense. Hence, we try to identify strong links by looking for preferential lending relationships expressed by discounts in the loan rate. Furthermore, we estimate the dynamics of credit spreads for each bank and find that economically significant spreads for the overnight market only developed in 2010. The analysis of bilateral loan relationships reveals that in the pre-crisis era large net borrowers used to borrow at a slight discount. In the post-Lehman era borrowers with large net exposures paid more than the average market rate, which shows that the risk evaluation of market participants has changed considerably.

Keywords: interbank markets, overnight loans, preferential lending

JEL classification: G15, G21, E44, G01

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May 11, 2012

1 Introduction

In this paper we investigate the lending behavior of banks in the Italian overnight loan market. Unlike in most other European countries in Italy, most of the overnight loans are settled by a central trading platform called E-mid. For our analysis we use tick data from this platform from the period 1999–2010. Although loans with different maturities are dealt over this system we focus on overnight loans, which are by far the biggest part of all transactions.

Since the 2008 financial crisis the overall interest in the linkages between banks has risen. Only little research was carried out before, some European markets have been analyzed for example by Iori et al. (2008), Boss et al. (2006), Furfine (2003), Hartmann et al. (2001) and Cocco et al. (2009). The U.S. money market system, Fed-wire, has been analyzed for example by Ashcraft and Duffie (2007).

The risen interest in these markets is twofold. On the one hand it stems from the observation of the partly collapse of interbank markets itself, the other reason is the increasing need for risk assessment in the bank network in general. The contagious effects that played a big role in the events after the Lehman default[1] showed that a micro-prudential analysis of banks' exposures does not

[1] The U.S. investment bank Lehman Brothers Inc. defaulted on 15th September 2008, marking the highpoint of the subprime mortgage crisis. It was followed by a sharp drop of all major stock price indices and financial market distress that necessitated massive bailout programs for banks around the world.

capture the systemic risks that the default of a bank can have.

Banks are of course connected through many different financial products, the analysis of overnight loans which we perform here is thus only a first step in understanding the networks of banks.

Until 2008 all bigger banks could relatively easy manage their short and medium run liquidity with various trading partners in different interbank markets. Since then the behavior of banks in the interbank market has changed dramatically. The volume in the interbank markets has fallen sharply, see, e.g., Gabrieli (2009) for the E-mid case, instead of a rise of spreads that would compensate for grown credit risks, we observed a shift from interbank market funding to funding by central banks. Very recent studies nevertheless show that interbank markets are still important, but that the trading activity has changed noticeably. These studies include Afonso et al. (2011) and Bech et al. (2011) for the federal funds market and Angelini et al. (2009) for the Italian market.

The earlier studies on the Italian market have already shed light on a number of statical regularities of trading behavior in the market. Also, we know that no pronounced clusters exit in the Italian market when conditional trading volume is analyzed, see Fricke and Lux (2012). The structure of the market can at best be described as a core-periphery structure, similar to the findings by Craig and von Peter (2010) for the German market.

Relatively little interest has been devoted to the analysis of interest rates from individual contracts. Hence, this paper will try to add some insights into the structure of this market by looking for preferential lending relationships between banks. Further we will look at how lending conditions and trading volumes developed over time and in which respect the market of today differs from the market as it was before the financial crisis. However, as a starting point we will have a look at the more general statistical patterns of trading activity.

2 Regularities in Trade Behavior

Figure 1 gives a first overview of the rates that are paid in the market. The average volume weighted daily mean is given by the solid black line. It follows

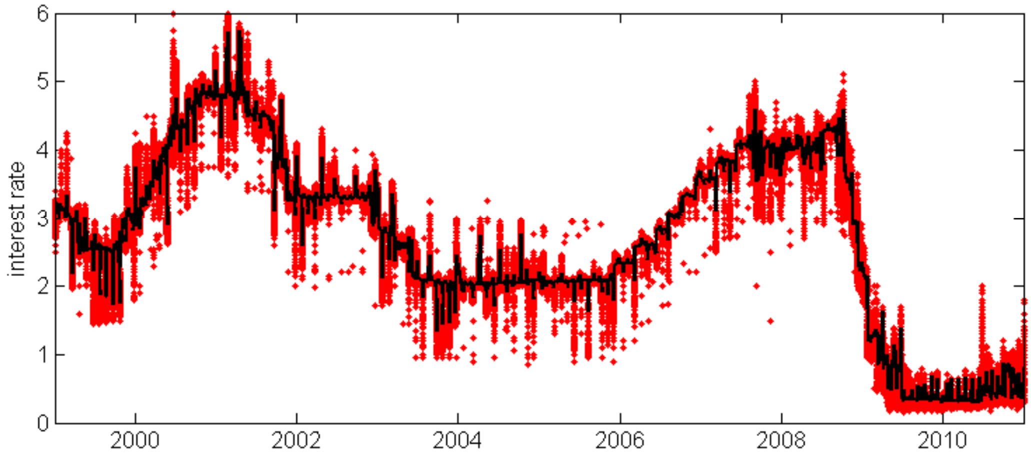

Figure 1: Interest rates in the E-mid market
The plot shows the daily mean rate in the black and every individual trade as a red dot. Cyclical peaks are visible at each end of the month. Overall most of the average rates are very close to the EURIBOR rate.

very closely the EURIBOR rate. Periodic peaks occur on and before every 24th of each month, when the banks balance their positions and report to the supervisor. Each single trade is marked by a red dot, the resulting red area shows the effective range of interest rates being paid. Almost all observations are within the band of the European Central Bank's deposit facility and marginal lending facility rate (for example for the period from June 2003 until December 2005 these rates were at 1% and 3%).

The daily and monthly patters of trading behavior are shown in Figure 2. Within the month we observe a slight increase in trading volume when we approach the 24th. The top left plot shows the number of trades for the days preceding the 24th with descending distance. The bottom left plot shows the dynamics of rate volatility. For comparable results we calculate the difference of each trade's rate from the average weighted daily mean and plot rates for the separate days. The red line indicates the standard deviation for each day. We observe the highest volatility of loan rates at the end of the month.

The daily trading patterns are very regular and are summarized by the top right plot. Pronounced peaks of trading activity are visible around 9 a.m. and 3

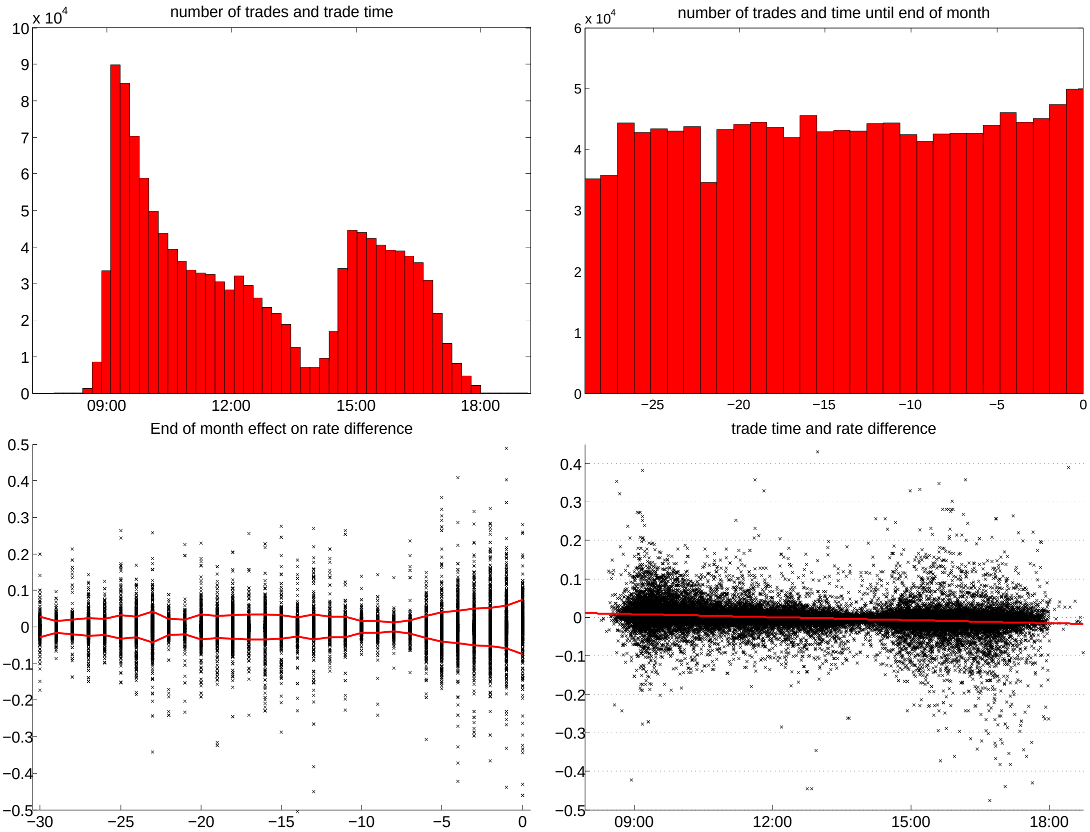

Figure 2: Regularities in trading behavior and rates during the day and month Top left: the trading activity shows a slight increase at the end of the month, Bottom left: the standard deviation of the average daily rate (red) is increasing at the end of the month, Top right: trading activity shows regular maxima in the morning and afternoon, Bottom right: the deviations from the average daily rate become negative during the day, as shown by the linear fit of the red line.

p.m. and a smaller one at 12:30 p.m., these can be explained first by office hours and secondly by the regular liquidity in and outflow that stems from the settlement of last day's E-mid trades and settlement from other trading platforms including the cash leg of securities. In general we can confirm the results of Iori et al. (2008).

At last we can look at the development of the average rates during the day. The right bottom panel shows a scatter plot, the average rate is slightly decreasing towards the end of the day, just as the maturity of any initiated contract is effectively decreasing by a few hours.[2] For a detailed analysis of the intraday development of loan rates see Baglioni and Monticini (2008).

3 Volatility and Trade Flows

An inspection of the interest rates over time reveals that trading behavior has changed significantly over the last years. Figure 3 shows a massive increase of volatility in September 2008 after a transition period that starts in early 2007. For this reason we start with looking at the market for the period from 1999 until 2006, to see how the market is organized in "normal" times and turn to an analysis of the dynamics until 2010 in Section 5

As a starting point we have a look at the number of trades and trade volumes for all market participants. We can plot the relationships between all banks as color coded values in a adjacency matrix. Every row in the plots in Figure 4 symbolizes one bank i and the entries in the columns give us information about the trades with every other bank j. The rows and columns in all plots are ordered first by nationality of the banks (first foreign banks, then Italian banks) and second by trade volume in ascending order. By definition an entry in row i column j can be interpreted as a relationship where bank i is the borrower in a contract with bank j.

From the two top panels we can infer two regularities of the market. First of

[2] For better visibility the two bottom scatter plots only show a random subsample of the dataset.

[3] The UK bank Northern Rock was faced with severe liquidity problems in September 2007 which finally lead to the bank becoming state owned to prevent a possible default.

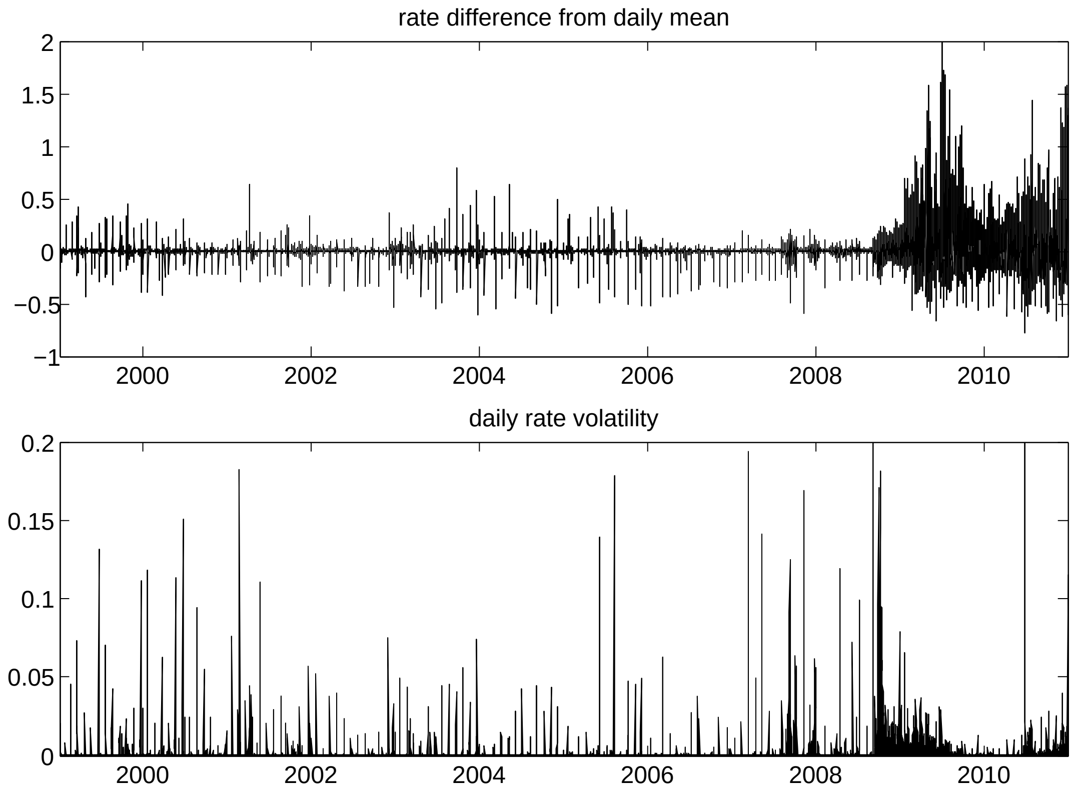

Figure 3: Interest rates and volatility over time
The top panel shows the difference from the mean daily rate for all trades. The bottom panel shows the daily volatility of loan rates. While for the period until early 2007 there are no permanent volatility increases, we see a change in late 2007, when with the Northern Rock bank run[3] volatility increases slightly, before in late 2008 we observe a drastic change in the market.

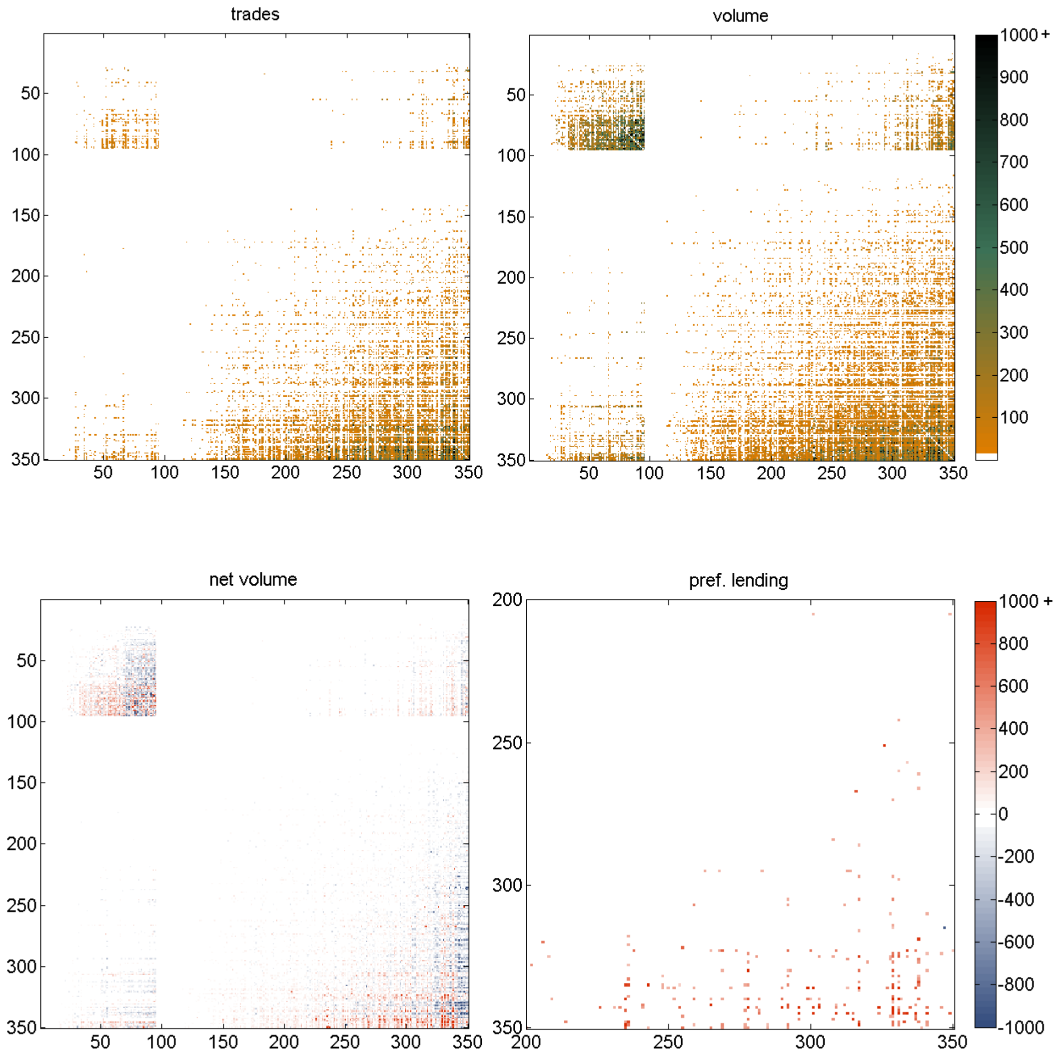

Figure 4: Trade flows, volume and net volume, 1999–2006
Top left: Number of trades, Top right: aggregate volume, identical values for the color coding of number of trades and volume in millions of Euro, Bottom left: Net volume, Bottom right: Net volume for preferential lending relationships from the estimation in Section 4. The rows and column are ordered: first into foreign and Italian banks, then by total trade volume. Row entries are borrowing transactions, column entries resemble lending. The plots show the asymmetry in lending, the banks with the highest trade volume are large net borrowers.

all, the foreign banks are much more visible in the right plot of aggregate trade volume than in the left plot showing the number of trades. The explanation is that the average volume per trade for foreign banks is significantly larger than for Italian banks. Obviously only larger foreign banks take part in the E-mid market. Secondly, the volume plot is far from symmetric. For the large banks at the bottom of the plot we observe pronounced borrowing activity which is not offset by an equal amount of lending, that should show as dark entries in the rightmost columns. To clarify this issue, the bottom left plot shows the net amounts that result from all trades. This plot is symmetric by construction. We observe that the banks with the largest trading volume are mostly net borrowers in the market.

The loan transactions that we have just seen expressed by a plot of the adjacency matrices can of course be interpreted as a network between the banks in this market. Two problems arise when one wants to map these relationships into a meaningful graph. For very short periods of time aggregation the resulting networks are very volatile and show a high level of randomness. Since thousands of transactions take place on a single day, the aggregation of trades over a longer time span will result in network representations where every bank with some activity will be connected to a very large share of the market participants. From the economic view point there is nothing wrong with this finding. It shows that the market is efficient in the sense that excess liquidity is distributed in the absence of noticeable market segmentations.

A resulting network representation is shown in Figure 5. To get an impression of the most important ties in the lending network from 1999–2006 we only consider links that correspond to a minimum of 250 borrowing transactions. As a result we see the strongly connected cluster of (mostly) Italian banks. Some hubs are visible in the core of this network, most of them are characterized by a high in-degree, which reflects the lending asymmetries discussed above.[4]

[4]The visualizations of the networks was performed using the software Pajek and the algorithm by Kamada and Kawai (1989) which produced a planar representation of the graph by minimizing the length of the edges.

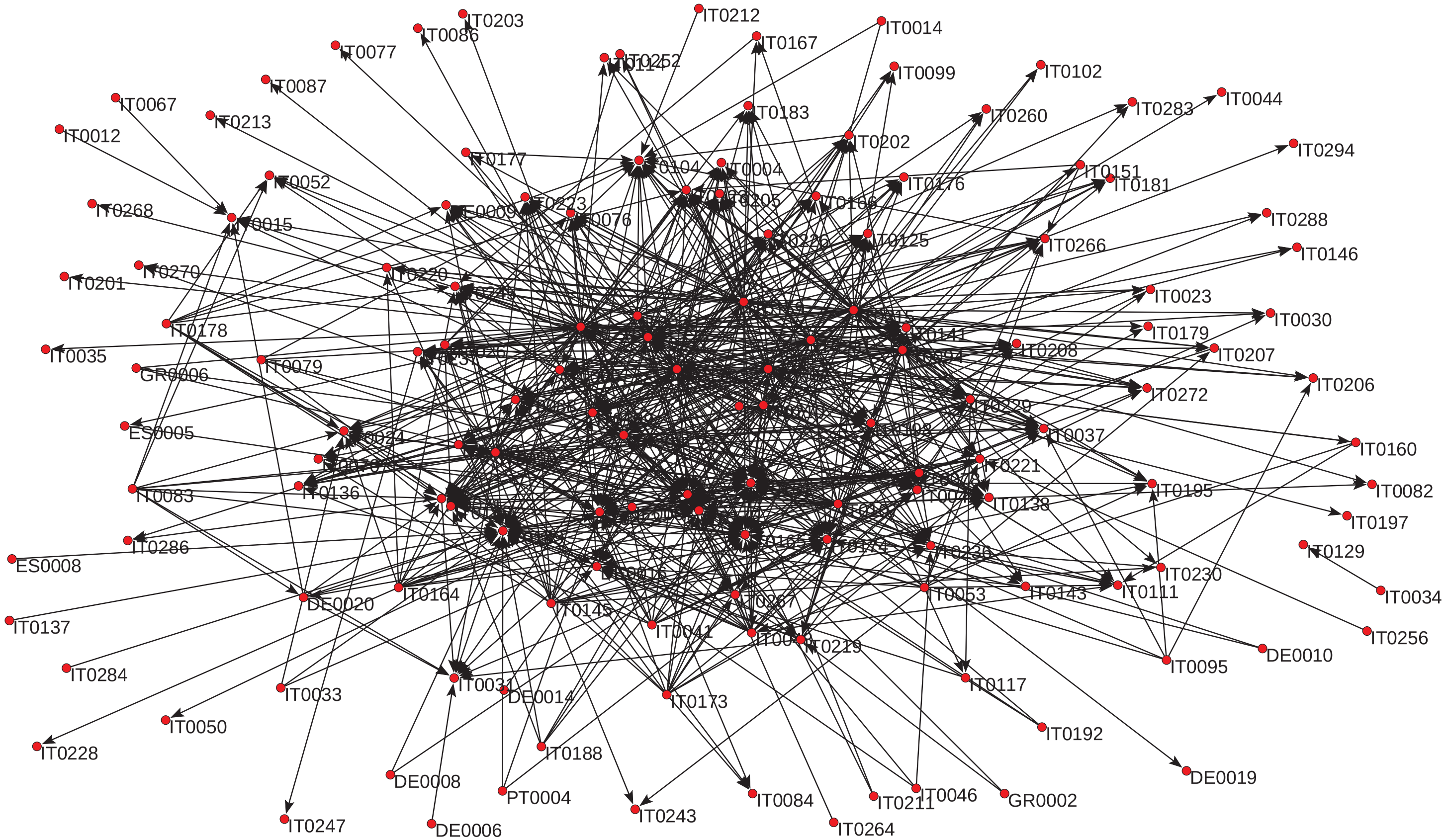

Figure 5: Network of Italian banks 1999–2006

The figure shows a dense network with some noticeable hubs characterized by a high in-degree. Arrows point at the borrower in a lending relationship with at least 250 transactions.

4 Estimation of Credit Spreads and Preferential Lending Relationships

4.1 What Loan Rates Can Tell

The relatively large dataset with about 1.3 million observations allows us not only to investigate trading patters, we can of course also investigate if banks trade at loan rates that differ significantly from the mean. For the years until 2006 the spreads for overnight loans cannot be expected to be very large since the counterpart risks for a one day loan are rather meaningless. Nevertheless, the range of banks that trade in the market is large, we have some global players but also some very small institutions, hence, some difference in risk should be priced in at least in a long run average.

In case that banks trade with each other very often, we can also analyze if the trading for this pair results in loan rates that differ from the average, conditional on the individual spreads and some other control variables. Significant deviations for pairs of trading partners can then be interpreted as a situation where preferential lending takes place between couples of banks. This analysis of "friendly" relationships could help to distinguish "random" trading relationships from those where institutional or personal ties play a role.

4.2 Estimation

The varying volatility in the market is of course a problem for the estimation, thus, similar to Cocco et al. (2009) we use the daily volatility to normalize the basis point interest rate differences that is our dependent variable. The remaining intraday volatility fluctuations are rather unsystematic. To obtain values that can be interpreted similar as interest rates we multiplied the standardized rate differences by the average of daily volatilities. The resulting variable is bpd. Further we discard the observations from the last day of each month and single days with an extremely high volatility, since trading behavior here differs noticeably from "normal" days and is of no help for our estimation.

As in most high frequency financial data we observe strong dependence. In contrast to stock markets, where the squared price changes show long lasting autocorrelation as a consequence of long memory in volatility (see, e.g., Engle and Russell, 2010), our data shows this feature even in the raw price changes. Since we are only interested in effects that happen on top of some autoregressive process, we estimate different versions of our model and compare the results to check for robustness

In the "simple" model we account for autocorrelation in the data by taking a weighted average of the last 8 trades, denoted $\overline{ar}$ to filter for autocorrelation[5]. We can then further estimate the bid ask spread in the data, ba, the influence of the log traded amount am, the influence of trading time tm, and the day, given by the difference until the end of the month EoM (the last three all as deviations from their mean values, day and time measured in units of days). For all the roughly 180 banks with at least 250 loan contracts we can estimate their spread by adding a matrix of dummy variables B. This matrix then has 180 columns with entries in B_{ti} if bank i is the borrower in contract t. Similar we can estimate pairwise relationships and add the dummy matrix $P_{ty(i,j)}$, where P has as many columns y as we have couples of banks i and j where bank i is borrowing at least 250 times from bank j. This results in estimating

$$bpd_t = \beta_0 + \beta_1 \overline{ar}_t + \beta_2 ba_t + \beta_3 am_t + \beta_4 tm_t + \beta_5 EoM_t + \gamma B_t + \eta P_t + \epsilon_t \qquad (1)$$

In order to get an idea of the influence of the standardization procedure we also estimate this model with a filtered version of the raw loan rate differences. The sample here gets smaller, because we filter all trading days where the volatility is larger than 0.0005, a value that produces a time series where the heteroskedasticity seems not too bad. Further we estimate the model also without P to make sure the estimation of bank fixed effects and preferential lending are independent.

The simple model actually works very well for the short run autocorrelation but for longer horizons some remains visible. In the "extended" model the autoregressive process is specified in a bit more detail. Similar to the so-called

[5]The weights were derived from the coefficients when estimating the model with 8 lags. Hence the result is the same as estimating the model with 8 separate lag terms, but a weighted average has shown to be more stable when adding all other variables.

HAR model by Corsi (2009) we model the autoregressive process with variables that cover different parts of the lag structure. In addition to the $\overline{ar}$ term, which reflects the current market price, we introduce $\overline{ar}^q$ and $\overline{ar}^h$ which reflect the average price differences from the last 15 minutes and the proceeding hour of trading. The extended model can be written down as

$$bpd_t = \beta_0 + \beta_1 \overline{ar}_t + \beta_2 \overline{ar}_t^q + \beta_3 \overline{ar}_t^h + \beta_4 ba_t + \beta_5 am_t + \beta_6 EoM_t + \gamma B_t + \eta P_t + \epsilon_t \quad (2)$$

In this model the effect of time tm cannot be estimated since this would conflict with the long run rate variable $\overline{ar}^h$. When we test this specification of the model and regress only on the ar variables, we see that it removes the autocorrelation better than the simple model, not to say perfectly. However, when we add all our dummy variables we see from the DW statistics that the filtering is acceptable but not as good. The likely reason for this is that also our dependent variables show some autocorrelation which might lead to a slight underestimation of $\overline{ar}$. This effect can be dampened by removing trades from the dataset where one bank is the borrower in successive trades. Essentially this mean that we remove trades that are likely to result from order splitting.

In general one should keep in mind that the micro-structure of this loan market differs from, for example, stock markets in two decisive ways. First of all, unlike stocks, loans are not a perfectly homogeneous good; if a lender wants to make a loan contract depends on the credit quality of the borrower and possibly on his already existing exposure to this borrower. Secondly, the market is not anonymous, the counterparts of a trade know each other, and might negotiate about a trade before settling it on the E-mid platform (see also Beaupain and Durré, 2008). This is likely to lead to a sluggish reaction to price movements. While new prices are quoted several times within a minute in busy trading periods, the effective time it can take to negotiate and process a trade is likely to be a bit higher, say, in the order of minutes.

indep. variable	raw data	std. data	std. data	ext. model
$const$	.2367	.2162	.2290	.1135
	(31.5)	(28.3)	(30.8)	(18.2)
$\overline{ar}$	.6506	.6698	.6662	.4302
	(689.9)	(867.2)	(882.9)	(277.3)
$\overline{ar}^q$				.3034
				(159.7)
$\overline{ar}^h$				.1172
				(74.2)
ba	.4909	.4686	.4422	.5472
	(272.5)	(333.3)	(313.1)	(318.4)
am	.0707	.0654	0.0498	.0496
	(83.1)	(97.2)	(67.8)	(62.3)
tm	-.2453	-.1765	-.2239	
	(-30.7)	(-28.2)	(-35.7)	
EoM	-.0015	-.0006	-0.0006	.0002
	(-15.9)	(-8.1)	(-8.3)	(2.2)
B	#172	#189	#189	#176
P			# 755	#412
obs.	660,155	949,013	949,013	663,264
DW	1.98	2.00	1.98	1.91
σ^2	.3700	.3336	.3166	.2935
R^2	.6416	.6408	.6590	.6724

Table 1: Regression results

Results from the OLS regression. The left column contains the results for the raw data model, the two center columns results for the standardized data simple model. The results for the extended model are in the right column. T-values are in parentheses. The number of variables for the borrower fixed effects B and preferential lending P are shown below. The estimation results for these variables are summarized in Figure 6 and 7.

4.3 Results

Table 1 shows the OLS estimation results for four versions of the model. A constant is needed because the volume weighted average daily mean rate differs from the unweighted average over all trades. The coefficients β_1 to β_6 are all significant (mostly on the 99% level) and have the expected sign. The difference of the results for the models using raw data versus the standardized data are visible but they still yield comparable results. Since more volatile trading days have been filtered from the raw data sample the coefficient for the autoregressive term is still a bit larger than for the standardized data model. The same effect might explain the difference in the coefficients for time tm. The influence of the day EoM seems to be limited on the volatility pattern we saw in the previous section, from the table we see that the influence is very small and the exact result seems to depend on details of the model specification and the filtration of the dataset.

The estimation results are stable when adding the preferential lending fixed effects P, none of the other variable changes sign, changes in the coefficients are negligible, given that we triple the number of variables in this step.

In the extended model most of the split orders, which come predominantly from the larger banks, have been removed. As a consequence the sample contains relatively more trades from small banks, which results in a higher average loan rate. Due to the lower number of observations fever relationships (P) can be estimated. The DW value is slightly worse than for the simple model, because it only accounts for autocorrelation on lag 1.

To compare the simple and the extended model in a bit more detail we checked if the estimated fixed effects γ and η are similar. In fact the bank fixed effects are almost identical, although the sample size for the extended model is much smaller. The estimation results for preferential lending relationships show some variations, here the absolute values seem less reliable, but the classification into preferential versus non-preferential relationships is rather robust. For details see Figure 14 in the appendix.

To check for the significance of the results we perform a simple bootstrapping experiment for both, the bank fixed effects γ and the preferential lending

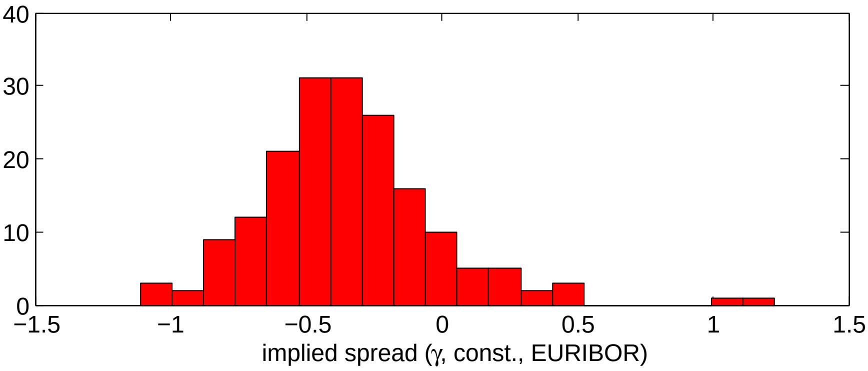

Figure 6: Implied credit spreads
The histogram shows the implied credit spreads for the period 1999–2006. The reference point is the EURIBOR rate. The average rate in the Italian market was on average marginally below the EURIBOR rate, most banks trade within a range of 2 bps.

relationship fixed effects η. This is done by separately re-shuffling the dummy matrices B and P and repeatedly estimating the model with these randomized dummy matrices. An alternative p-value can than be calculated from the bootstrapped distributions of the resulting γ and η. The results confirm the p-values calculated from the t-statistics.[6]

The distribution of borrower fixed effects γ, which can be interpreted as credit spreads are shown in Figure 6. Here we show them as the difference from the EURIBOR rate. Obviously most of the banks borrow within a band of 2 bps, which is not much. However it is important to account for these effects before we turn to the pairwise bank relationships, which would otherwise be overshadowed.

The influence of preferential lending finally is shown in Figure 7. The distribution of preferential lending effects is biased towards negative values. This is

[6]For η for example, a coefficient value of .059 marks the 95% confidence from the bootstapping experiment while the t-statistics suggest a value of .58 (assuming the same average variance). Alternatively the dummy variable P can be shifted in time, which conserves the autocorrelation. In this case the bootstrapped distribution of η becomes slightly assymetric and the bounds for the 95% interval are -.07 and .06. To summarize, this indicates that the significance of the estimates are (if at all) most likely only slightly overstated by the regular t-statistics.

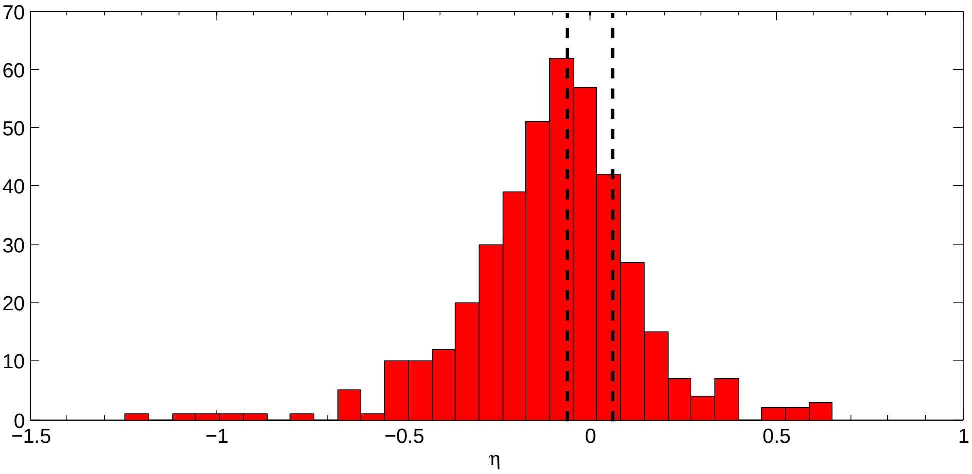

Figure 7: Estimated coefficients for frequent trading relationships
The Histogram shows the estimated deviations of the interest rate for trading relationships with at least 250 trades. The 95% confidence interval is indicated by the dashed line. The distribution is biased towards negative values which means that the majority of frequent trading relationships comes with a slightly lower loan rate. Values derived from the extended model.

not totally unexpected, because in this subsample large banks should be overrepresented, remember that only relationships with a minimum of 250 borrowing transactions are estimated. We can visualize these preferential lending relationships by looking at its adjacency matrix. A plot with all relationships where the loan rate was significantly lower (95% conf. level) than the average is shown in the bottom right panel in Figure 4. The plot shows the net volume for these lending relationships (in this plot the bottom right part of the adjacency matrix is magnified). The most frequent lending relationships are characterized by one-sided borrowing activity. Significant deviations from the mean loan rate occur only for Italian banks. Preferential lending, as shown in the plot, happens predominantly when top 30 banks borrow from smaller Italian banks or from other banks with very high market volume.

We can also show the network of these preferential lending relationships in Figure 8. The network is dominated by unidirectional links to big hubs, these banks steadily suck in the excess liquidity from smaller banks, which obviously

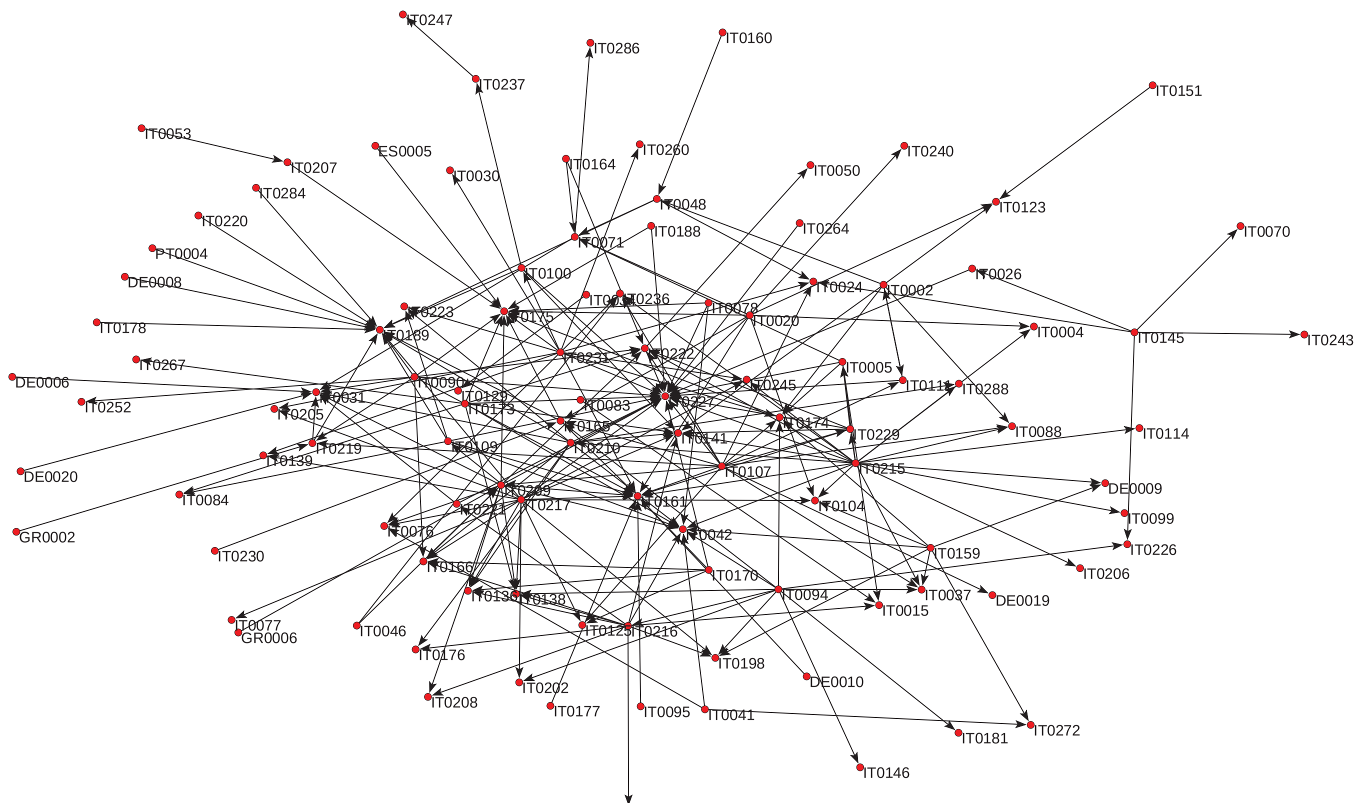

Figure 8: Network of preferential lending relationships
The network of preferential lending relationships has about half as many links as the trade network. The maximum degree is significantly reduced and the links of the central hubs are limited to the most important trading partners. Links derived from the extended model.

leads to some kind of preferential relationships. These relationships expressed by slight discounts in the interest rates are small, so they might not be of big economical importance for the single bank, nevertheless they become visible in our data. Lending relationships which are presumably of a more random kind are filtered out in this network representation. Conversely, lending relationships that result in higher then average loan rates result from lending from more peripheral banks. The resulting network of these non-preferential lending relationships does not have a dense core and is much more segmented than the latter network, see Figure 14 in the appendix.

5 Lending Dynamics and Financial Crisis

5.1 Development of Credit Spreads and Volume Dynamics

In the following we turn to an analysis of the market dynamics over time and to the changes that have been induced by the ongoing financial crisis. We start with the estimation of credit spreads on a year by year basis.[7] The plots in Figure 9 reveal that the number of trades (and volume) has a decreasing trend that even accelerates in 2008. The number of banks for which we can estimate the spread is thus also decreasing. While the range of spreads, measured by the standard deviation of γ, are very low until 2007, we see a sharp increase afterwards and a slightly puzzling dip in 2009.

Since the composition of the sample shows some churning over time we should also look at the sample of 14 banks which are very active throughout the whole time in Figure 10. The fixed sample confirms our results, while spreads are relatively low until 2007, 2008 shows a slight amplification. In 2010 we see a much more differentiated picture. This panel also reveals that 2009 is characterized by an slight increase in the spreads (relative to EURIBOR) which affects all banks similarly, and hence leads to a drop in the standard deviation of spreads (see also Figure 16 in the Appendix). The results for 2009 might also suggest that

[7] We use the simple model since this is more efficient for smaller samples and we have seen that the results for the borrower fixed effects do not differ significantly from the extended model.

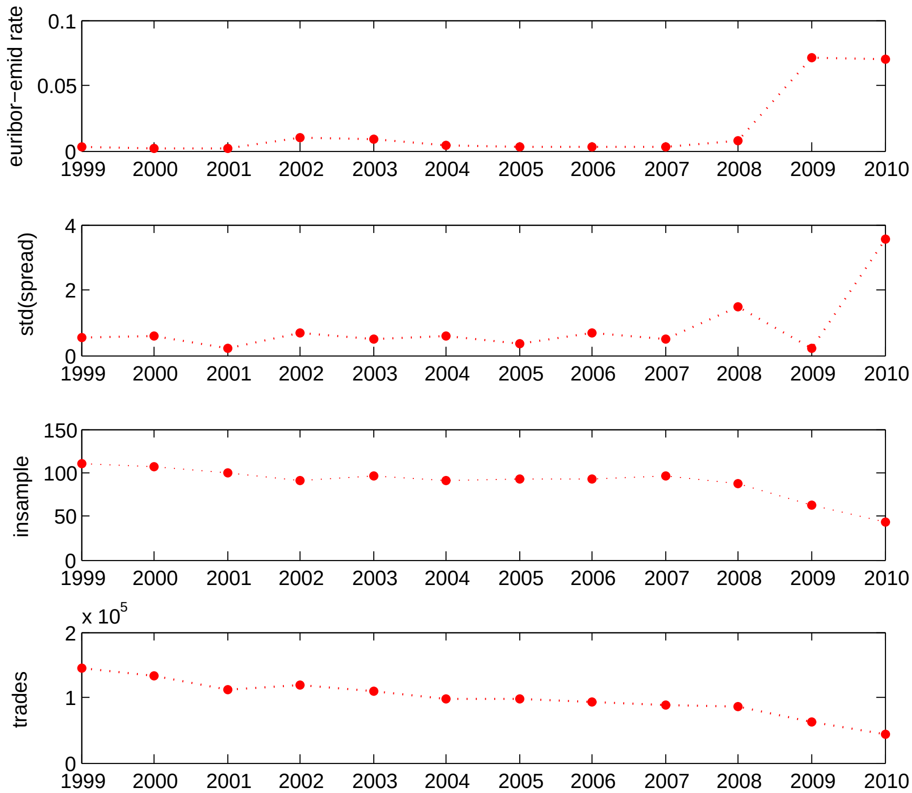

Figure 9: Credit spreads over time
Panel 1: The difference of the average E-mid rate and the EURIBOR rate is rather small, an increase is visible after 2008. Panel 2: The standard deviation of estimated credit spreads is increasing in 2010 after noticeable changes in the spreads in 2008 and 2009. Panel 3: The number of banks with at least 200 trades is decreasing steadily, the process accelerates in 2008. Panel 4: The number of overnight trades on the E-mid platform is declining from around 135,000 in 1999 to 45,000 in 2010.

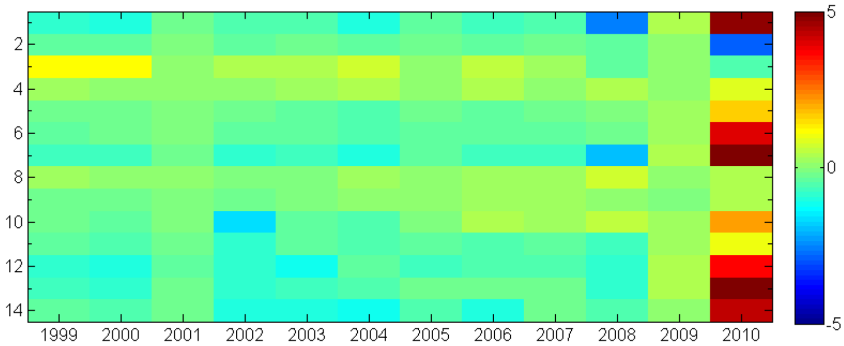

Figure 10: Credit spreads over time, fixed sample
The panel shows the color codes spreads with the EURIBOR as a reference for the 14 banks which are constantly trading on E-mid from 1999 until 2010. In 2008 the spreads become a bit more pronounced, in 2009 we observe an increase of spreads which equally effect all 14 banks. In 2010 spreads are again widening and increasing. We observe a reordered ranking of the implied rating of the banks.

instead of trading at a higher rates, banks choose not to trade if all, if possible, and used the central banks for their refinancing operations (see also Gabrieli (2009) for this issue).

We can also look at how much the positions and trade shares within the network have changed from year to year. Denote by $V_{[N \times N]}$ the matrix of aggregate trade volumes between the N banks in our network, then the share of total volume RV_{ij}^t that bank i borrows from bank j in year t can be expressed as

$$RV^t = \frac{V^t}{\sum_{i=1}^N \sum_{j=1}^N V^t} \tag{3}$$

and the change in relative volumes is given by

$$\Delta RV^{t,t-1} = \frac{\sum_{i=1}^N \sum_{j=1}^N \left| RV^t - RV^{t-1} \right|}{2} \tag{4}$$

For ΔRV a value of 0 corresponds to a situation where the volume shares have been unchanged, the maximum value is 1 and describes in situation where every bank changed all trading partners.

For the dynamics of the net positions we first have to calculate the net volumes as $NV^t = V^t - (V^t)^T$. Since we only want to compare the net borrowing for banks which were trading with each other in two successive years we filter the net volumes such that we use only those entries from the matrix which were non-zero for both years, hence $NV_{ij}^{F,t+1} = NV_{ij}^{t+1}$ if $V_{ij}^t > 0$ and 0 otherwise, conversely for $NV^{F,t}$. Then the relative net volumes are given by

$$RNV^t = \frac{NV^{F,t}}{\sum_{i=1}^N \sum_{j=1}^N |NV^{F,t}|} \tag{5}$$

and the change in these net volumes can then be calculated as

$$\Delta RNV^{t,t-1} = \frac{\sum_{i=1}^N \sum_{j=1}^N \left|RNV^t - RNV^{t-1}\right|}{2}. \tag{6}$$

This measure is also bound between 0 and 1. Changes in total volume from year to year do not have a direct effect on these measures, since we treat all quantities as shares of the annual total amounts.

Finally we can calculate the ratio of net positions to total volume NTV as

$$NTV^t = \frac{\sum_{i=1}^N \sum_{j=1}^N \left|NV^t\right|}{2\sum_{i=1}^N \sum_{j=1}^N V^t}, \tag{7}$$

which tells us how much of the lending volume in the market stems from lending relationships which do not net out within one year.

The top panel of Figure 11 shows the volume differences. For most of the time about one half of the relative volume was shifted to other trading partners from year to year, the rate is increasing heavily after 2008. The development of relative net volume changes in the middle panel shows a different behavior. We see a first dip here in 2002. This coincides with the year when more foreign

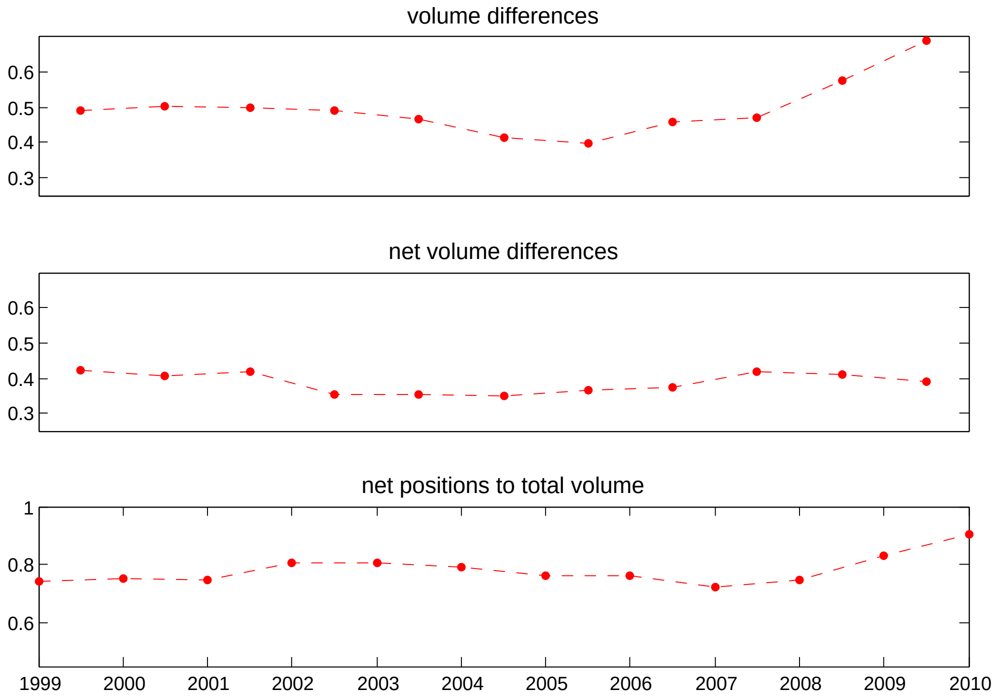

Figure 11: Volume dynamics

Top panel: The share of relative volumes differences in borrowing relationships varies between 0.4 and 0.5 until 2008, after then it increases to 0.7; we observe in increasing change of trading partners. Middle panel: The change in relative net volume differences is relatively stable at around 0.4. We observe a slight decrease in 2002 when more foreign banks enter the market and a slight peak from 2007 to 2008. Bottom panel: The ratio of net positions to total trading volume is increasing to 0.9 after is was between 0.7 and 0.8 until 2008.

banks entered the E-mid market, see Fricke and Lux (2012). We observe a slight increase from then on until 2008, for 2009 and 2010 we see a slight decline, which is very interesting, because it does not follow the trend of the volume figures. The ratio of net positions to total volume in the bottom panel explains most of this effect. While the market volume in general is shrinking, unidirectional lending is gaining relatively importance in the market, the ratio of net positions to total volume is increasing to over 90% after a small dip in 2007.

5.2 Lending in the Post-Lehman Market

Finally we can repeat our analysis of trade flows and preferential lending relationships for the post-Lehman period. Figure 12 shows the number of trades, volume and net volume with the color coding similar to Figure 4. The number of trades and volume have experienced a noticeable drop, yet the asymmetric lending pattern among the Italian banks is still visible.

We have already discussed the estimation of credit spreads on a year by year basis, thus we can now directly turn to the estimation of preferential lending relationships for the entire period of August 2008 – December 2010. The distribution of η, the coefficients from the estimation of frequent lending relationships is shown in Figure 13. For this period the histogram is biased towards positive values, which is in sharp contrast to the results for the period from 1999 until 2006.

The nature of the transition that took place in the market becomes more clear when we again plot the adjacency matrix of these relationships. Instead on focusing on the lending relationships that result in lower rates, we have a look at those which result in slightly higher rates, the "non-preferential" lending. The bottom right plot of Figure 12 shows that now many of the one-sided borrowing relationships, which until 2008 lead to slight discounts in the loan rate, trade at a small premium (see Figure 17 for a network representation). The interpretation of this change is straightforward, the basic pattern of the market is that we have some large banks with a huge net liquidity (refinancing) demand and large group of relatively smaller banks with some excess supply. As long as the economic situation was stable and counterparty risks were negligible, the small

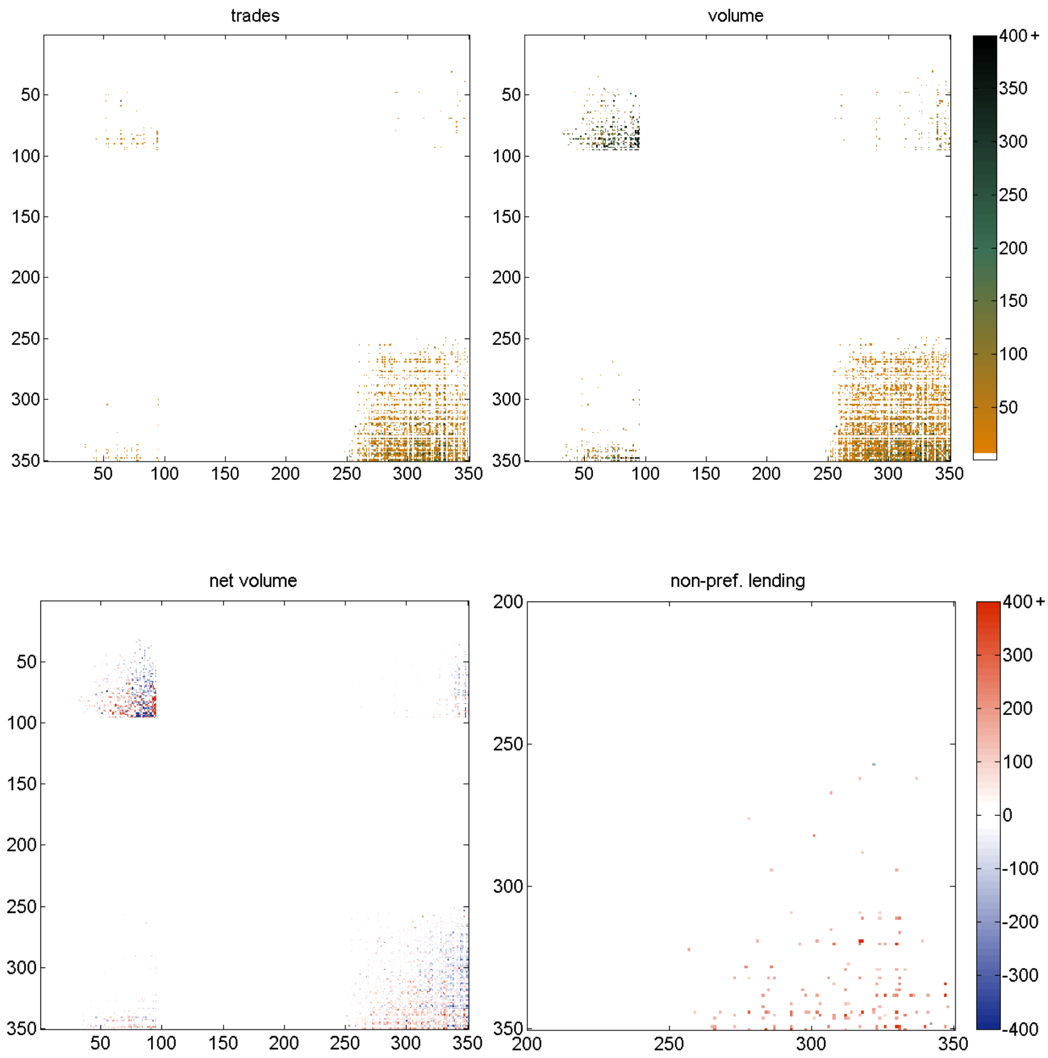

Figure 12: Trade flows, volume and net volume, post-Lehman
Top left: Number of trades, Top right: aggregate volume, Bottom left: Net volume, Bottom right: non-preferential lending relationships. The rows and columns are ordered: first into foreign and Italian banks, then by total trade volume. Row entries are borrowing transactions, column entries represent lending. The trade volume has decreased, some banks have left the market.

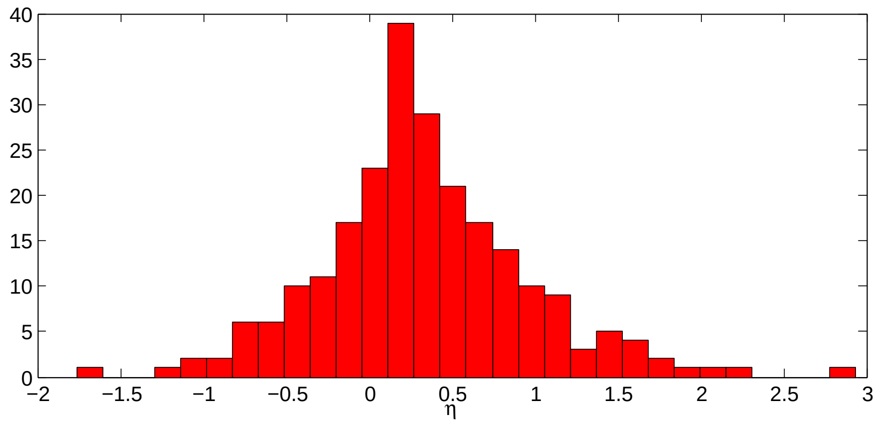

Figure 13: Distribution of η for the post-Lehman period
The histogram of η shows that for the past Lehman period lending relationships with at least 80 trades have a bias for rate premia. The threshold is scaled down to account for the shorter time horizon and the smaller average number of trades.

banks were reluctant to lend to the big banks. After 2008 the basic situation of excess demand and supply was the same but most likely the risk assessment has changed. Lending relationships with a permanent net position of one of the parties now tendencially lead to slightly increased loan rates.

6 Discussion

The Italian interbank market has undergone significant changes during the last 12 years. After its start it could attract not only Italian banks but also a number of foreign banks joined the market. Some smaller banks have left the market, this might be a result of merges and acquisitions activity, some of them might also have transfered the refinancing and liquidity management to larger affiliated banks.

The trading volume in the market went down significantly, especially since interbank markets became stressed in 2008. A noticeable change is that we can observe economically significant spreads in the market since 2010. After Angelini et al. (2009) have already observed a widening of spread for loans with a longer maturity, this could be a signal for a changing risk assessment of banks also in the overnight market. One could draw the conclusion that until 2007 banks would be willing to lend to anyone on the overnight market with some reputation and that in 2008, when a day-to-day monitoring of the counterparts became necessary, because there was suddenly a much higher risk of default, they were not capable of this monitoring, or it was too costly.

A changing behavior is also observed for the very frequent trading relationships. While we see slight discounts from these relationships until 2006, the reverse happens from 2008 until 2010. The net exposure to a borrower is now something that is associated with an additional risk that is priced into the loan rate, additional to the overall borrower specific spread.

Methodologically we have seen that it is possible to combine approaches from network science, like the analysis of flows and network structure, with approaches from empirical economics, the analysis of interest rates, in a complementary way.

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Appendix

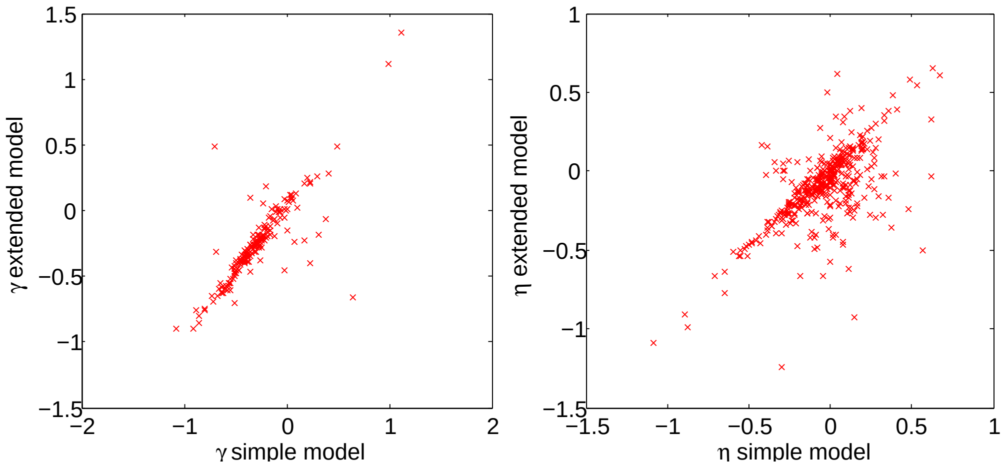

Figure 14: Comparing γ and η for the two models
The coefficients of the bank fixed effects in the left scatter plot ($n = 176$) are mostly close to a 45-degree line. The comparison of the preferential lending fixed effects $n = 412$ looks a little bit more noisy, still only about 5% of the observations are far from the 45-degree line.

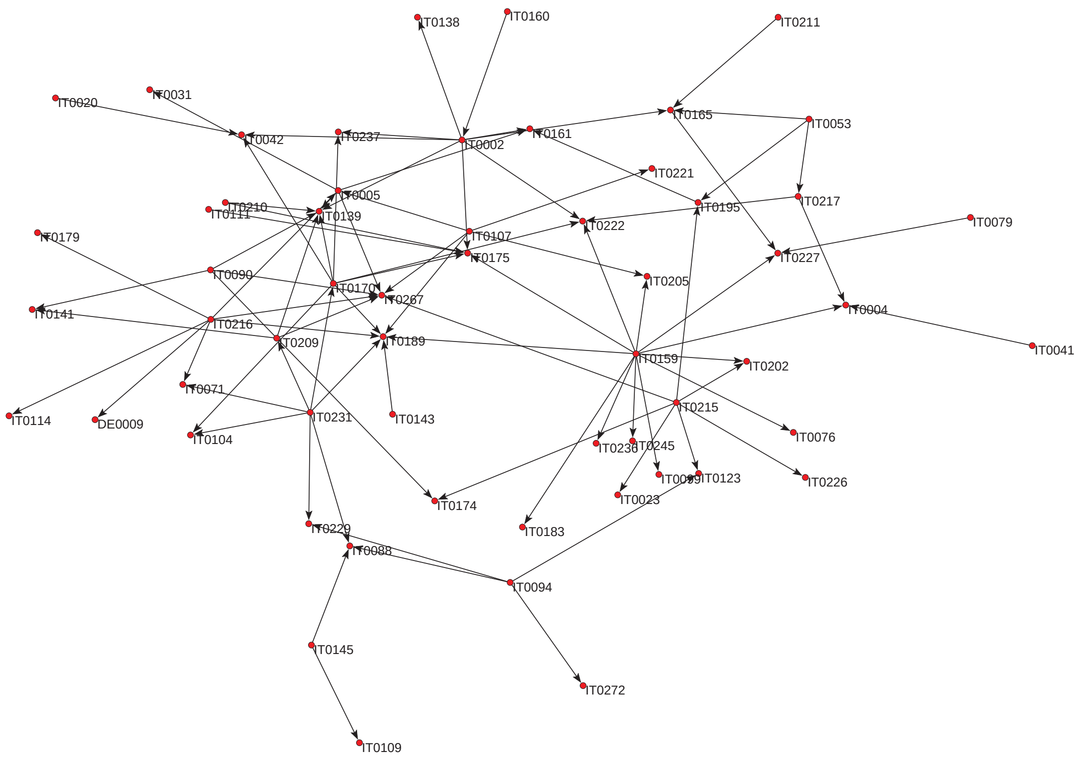

Figure 15: Network of non-preferential lending, 1999–2006

The “network of enemies” has a very special structure. Instead of a connected core we observe an almost circle like network with hubs that connect to the periphery but have relatively little links to other core hubs.

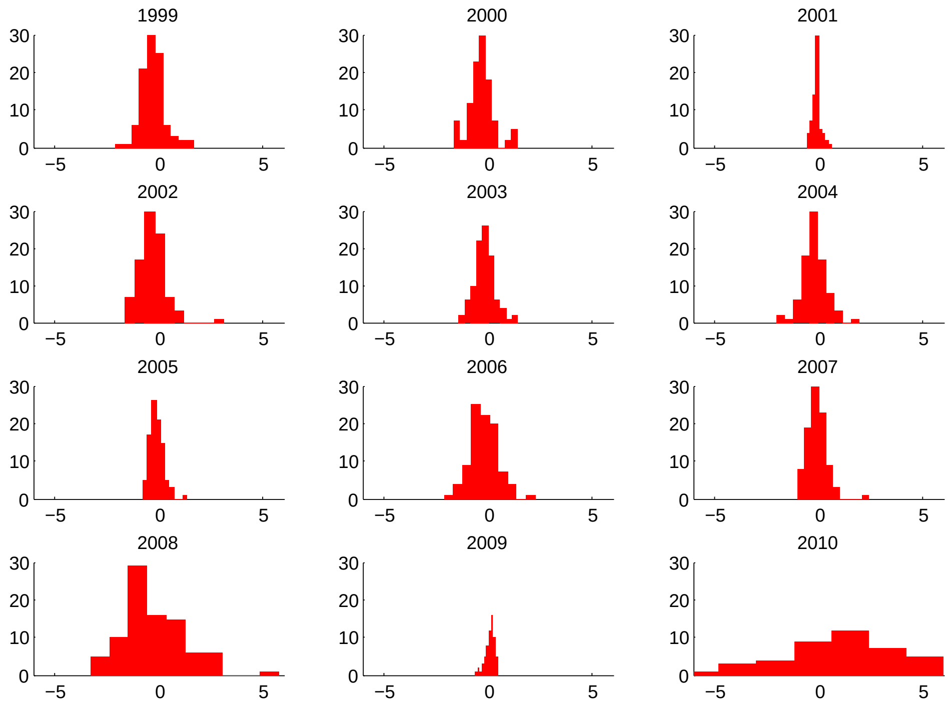

Figure 16: Spreads year by year
The histograms for the year by year estimated γ show similar distributions for 1999–2007 (exception: 2001). In 2008 amd 2010 the range of spreads is much wider. 2009 shows an increase of the mean value but also a much narrower distribution.

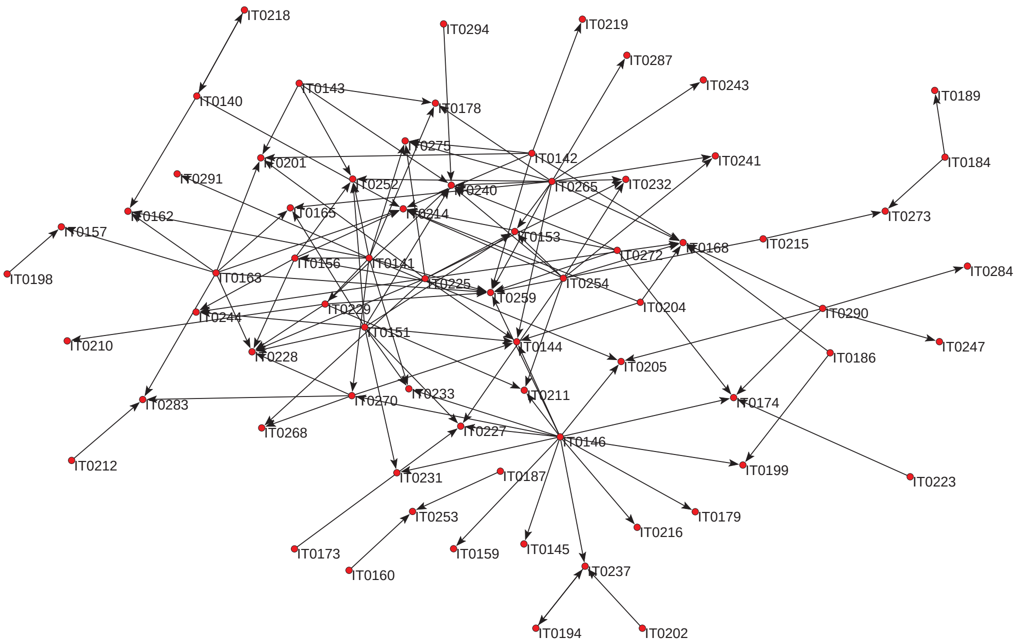

Figure 17: Network of non-preferential lending, post-Lehman
The network of non-preferential lending for the post Lehman period has similar characteristics like the network of preferential lending until 2006.