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## Lending relationships in the interbank market

João F. Cocco<sup>a</sup>, Francisco J. Gomes<sup>a,\*</sup>, Nuno C. Martins<sup>b</sup>

<sup>a</sup> London Business School, Regent's Park, London NW1 4SA, UK, and CEPR

<sup>b</sup> Universidade Nova de Lisboa and Banco de Portugal, Av. Almirante Reis, 71, 1150-012 Lisboa, Portugal

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### ABSTRACT

We use a unique dataset to show that relationships are an important determinant of banks' ability to access interbank market liquidity. More precisely, we find that: (i) banks with a larger reserve imbalance are more likely to borrow funds from banks with whom they have a relationship, and to pay a lower interest rate than otherwise; (ii) smaller banks and banks with more non-performing loans tend to have limited access to international markets, and rely more on relationships; (iii) relationships are established between banks with less correlated liquidity shocks. These results suggest that relationships allow banks to insure liquidity risk in the presence of market frictions such as transaction and information costs. Our analysis explicitly controls for the endogeneity of bank relationships.

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## 1. Introduction

Many interactions between economic agents are of a frequent and repeated nature. In such a setting agents may establish relationships, and equilibrium outcomes may be different from those that arise in an anonymous market. In a recent paper, Carlin et al. (2007) solve a dynamic model of trading based on liquidity needs. They show that cooperation is an equilibrium outcome of the repeated-game model. Cooperation involves refraining from predation and allows the trader who has suffered a liquidity shock (the distressed trader) to transact at more favorable prices. Their model predicts that the level of cooperation is an important determinant of traders' ability to access funds, and of the amount of liquidity available in the market.

Our paper studies the role (if any) of relationships in the process of liquidity provision in the interbank market. The importance of interbank markets as distributors of liquidity is well recognized in

\* Corresponding author.

E-mail addresses: [jcocco@london.edu](mailto:jcocco@london.edu) (J.F. Cocco), [fgomes@london.edu](mailto:fgomes@london.edu) (F.J. Gomes), [nmartins@bportugal.pt](mailto:nmartins@bportugal.pt) (N.C. Martins).

the literature. Ho and Saunders (1985) examine a model in which banks' reserve positions are affected by stochastic customers' deposits and withdrawals; interbank trading allows them to meet their reserve requirements. In Bhattacharya and Gale (1987) interbank market trading also provides insurance against inter-temporal liquidity shocks. Similarly, in Allen and Gale (2000) liquidity shocks arise from uncertainty in the timing of depositors' consumption, whereas in Freixas et al. (2000) liquidity risk arises from consumers' uncertainty about where to consume. A common feature to these models is that a well functioning interbank market is important for banks' ability to access liquidity, and as a result, it is important for firms' and consumers' ability to access bank financing, and ultimately for the efficiency of the financial system.

The interbank market is a natural setting to study the question of whether relationships play a role in the process of liquidity provision. The interbank market is fragmented in nature. For direct loans, which account for most of the market volume, the loan's terms are agreed on a one-to-one basis between borrower and lender. Other banks do not have access to the same terms. When quotes are posted on screens, they are merely indicative. In addition, there are frequent and repeated interactions between the same banks. This market structure allows relationships to play an important role.<sup>1</sup>

In order to study this question we use a unique dataset that contains information on *all* direct loans that took place in the Portuguese interbank market between January 1997 and August 2001. The Portuguese market is smaller than the Fed Funds and most Euro area interbank markets, but its market structure is similar to that of these larger markets. Our dataset contains comprehensive information on each loan (date, amount, interest rate, maturity, and identity of lender and borrower). These data allow us to track loans between each and every pair of banks over time, information that we use to construct dynamic measures of relationships, based on the intensity of pair-wise lending activity. Our data also include daily information on banks' reserve deposits, and quarterly information on balance sheet variables such as total assets and non-performing loans. Finally, we also observe all financial flows between banks, other than interbank market loans, which we use to construct a measure of "other interactions" that take place between them.

Our results support the prediction that bank relationships are an important determinant of their ability to access funds, and of the amount of liquidity available in the market. First, we find that banks with a larger imbalance in their reserve deposits are more likely to borrow funds from banks with whom they have a relationship, and to pay a lower interest rate on these loans than they would otherwise. This result supports the prediction of Carlin et al.'s (2007) model that under repeated interaction, cooperation among banks is an equilibrium outcome that involves refraining from predation, and that allows those with a larger reserve imbalance to transact at more favorable prices.

Second, we find that small banks and banks with a higher proportion of non-performing loans tend to have limited access to international markets, and that they tend to rely more on relationships when borrowing funds in the domestic interbank market. This result is consistent with relationships allowing banks to access liquidity in the presence of market frictions, such as transaction and information costs. It provides support for the assumption of Freixas and Holthausen's (2005) model that information on foreign banks is coarser than on domestic peers, with whom inter-bank market relationships may have developed over a longer time period. We find evidence that these relationships are likely to extend beyond the interbank market. More precisely, we show that the relationship measure constructed using interbank market data is positively correlated with a measure of other relationships constructed using data on other financial flows.

Third, we use the information on each bank's reserve deposits to construct a measure of liquidity shocks which is equal to the daily change in these deposits. We find that banks with more volatile liquidity shocks are more likely to rely on relationships, and they tend to do so with banks which face less volatile liquidity shocks. Furthermore, we find that banks establish relationships with those banks with whom they have a lower correlation of liquidity shocks, which may further enhance the liquidity of the overall market. This is an important finding since Allen and Gale's (2000) model predicts that

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<sup>1</sup> The issue of price formation and the properties of prices in centralized versus fragmented markets has been the subject of much research (see for example Wolinsky, 1990 or Biais, 1993).

the financial system is less fragile when the correlation of liquidity shocks between banks that are related is lower.

Overall, our results support the prediction that relationships play an important role in the process of liquidity provision in the interbank market. The potential for these relationships to develop is an important advantage of bilateral markets relative to anonymous ones. This may help to explain why the interbank market seems to function well, even in periods of financial crisis (Furfine, 2002). In addition, our results provide support for the notion that it is important to take into account off-balance sheet variables (in our case, relationships), when evaluating the ability of banks to cope with liquidity risk.

Our analysis of the interbank market also uncovers a variety of patterns of trade that is consistent with evidence for the Fed Funds market. We find that large banks tend to be net borrowers, while small banks tend to be net lenders in the market (see Furfine, 1999; Ho and Saunders, 1985, for evidence on the Fed Funds market). We find that, controlling for the degree of lending relationship and holding the size of the counterparty fixed, larger banks trade at more favorable rates. In addition, borrowers with a higher proportion of non-performing loans tend to pay higher interest rates (Furfine, 2001).

On the methodological side, our analysis recognizes that the decision of whether to rely on relationships is an *endogenous* choice. We estimate instrumental variables regressions, in which we explore the time-series dimension of the panel by using lagged relationship measures as instruments, and a seemingly unrelated regressions system of equations, with the loan characteristics and the relationship measures as dependent variables. This allows us to simultaneously study the determinants of the terms of the loan and of relationships.

Our paper is related to the previously cited literature on the interbank market. There is also a literature on lending relationships that focuses on bank–firm relationships.<sup>2</sup> This literature focuses on long-term relationships between banks and firms, by which banks acquire inside knowledge about firm characteristics or the project that is being financed. Although somewhat related, it is important to note that these relationships are of a different nature than the ones that we study in our paper, which are transaction based. Our paper is also related to the papers which show that more regular customers tend to receive better allocations or prices when buying shares, both in primary markets (Cornelli and Goldreich, 2005) and secondary markets (Bernhardt et al., 2004). Although related, our paper differs from these in that it emphasizes the role of relationships in the process of liquidity provision. In this respect, our paper is closer to Battalio et al. (2005).

The paper proceeds as follows. Section 2 describes the data, our relationship metrics and reports summary statistics. Section 3 studies the pricing of interbank loans. Section 4 investigates the determinants of relationships. Section 5 presents additional evidence on these determinants, that allows us to be more precise with respect to their nature. Section 6 concludes.

## 2. The data

### 2.1. Description

We combine information from three different datasets, which we have obtained from the Portuguese Central Bank. The first dataset has information on all direct loans in the Portuguese interbank market from January 1997 to August 2001. This market has a similar structure to other interbank markets in the Euro area, and to the Fed Funds market. Each loan may be either borrower or lender initiated. When a bank wishes to borrow or lend funds, it approaches another bank, identifies itself, and asks for prices, i.e. interest rates, for borrowing and lending funds at a given maturity. It is very rare that banks asking for quotes are turned down, or simply refused funds. But banks do provide

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<sup>2</sup> This literature has found evidence that relationships help overcome constraints that arise from monitoring and default risk (Berger and Udell, 1995; Petersen and Rajan, 1995; Slovin et al., 1993), and they allow banks to provide insurance to firms in the form of interest-rate smoothing (Ongena and Smith, 2000; Berlin and Mester, 1999; Petersen and Rajan, 1995; Berger and Udell, 1992).

different quotes for different banks that approach them, and it is common practice for them to shop around for the best rates.

Our dataset is unique in that it comprises all direct loans, and contains information on the loan's date, amount, interest rate, and maturity, as well as the identity of the lender and the borrower. Being able to identify the lender and borrower for each loan, and to observe all loans over a long period of time, is crucial for our study of lending relationships. Even though interbank loans are privately negotiated, they must be reported to the central bank, who is responsible for their settlement, by debiting and crediting the reserve accounts of borrowers and lenders.

We restrict our analysis to overnight loans, i.e. loans maturing on the next business day. We do so because the interbank market is mainly a market for short-term borrowing and lending of funds: during the sample period there were 44,768 overnight loans accounting for over 75 percent of the total amount lent. And the vast majority of the remaining loans are also short term in nature: over the sample period there were only 2145 (303) loans with maturity longer than one month (six months). If we were to include these loans in the analysis together with the overnight loans, and given that such loans are very infrequent, it would be very difficult to calculate a valid benchmark or market wide interest rate. This is why we have decided to exclude such transactions from the sample, and to focus the analysis on the overnight loans.

One could question the appropriateness of measuring a long-term economic behavior—relationships—with something that is short-term in nature—overnight loans. However, we would like to note that even though the focus of the analysis are overnight loans, over the sample period there are frequent and repeated loans between the same banks. One may expect that under such circumstances relationships may be formed. Furthermore, we will present evidence that relationships based on overnight loans are part of wider relationship between banks. Finally, even though credit risk for loans of overnight maturity may be small, it is important to note that these are large and uncollateralized loans, with the average loan amount of roughly twelve million euros. Therefore we expect that even small differences across banks in credit risk are reflected on the loan interest rate.

The second dataset provides daily information on the balance in the banks' reserve accounts. It allows us to study how the banks' reserve position affects their behavior in the interbank market.

The third dataset contains quarterly information on bank characteristics, including total assets, financial and profitability ratios, and credit risk variables. This dataset also allows us to determine whether the bank belongs to a banking group, defined in terms of control of the institution. We exclude loans between banks belonging to the same group, which leaves us with a total of 37,701 overnight loans.

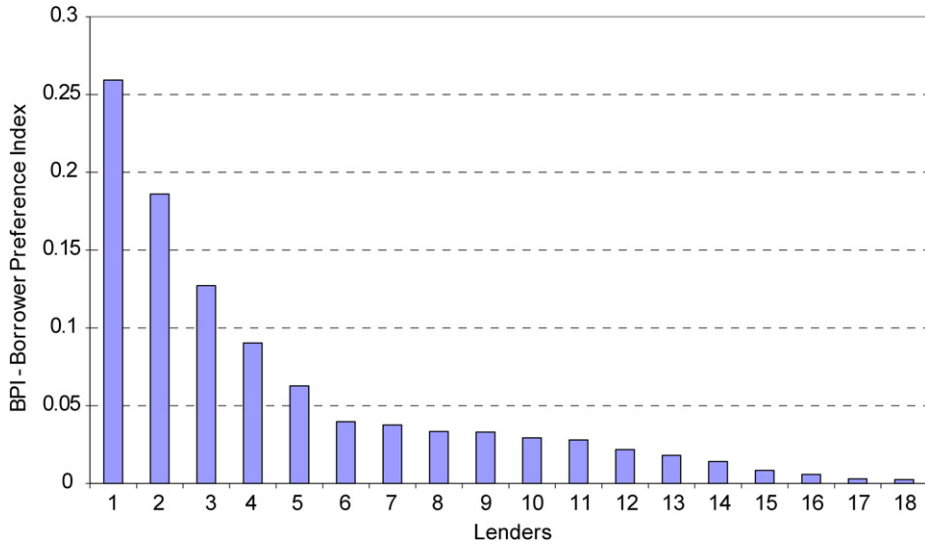
## 2.2. Measuring lending relationships

We measure lending relationships by the intensity of lending activity between banks. More precisely, for every lender ( $L$ ) and every borrower ( $B$ ), we compute a *lender preference index (LPI)*, equal to the ratio of total funds that  $L$  has lent to  $B$  during a given year/quarter, over the total amount of funds that  $L$  has lent in the interbank market during that same year/quarter. Thus each time period,  $t$ , in our analysis is a year/quarter. Overall there are nineteen time periods during our sample period.<sup>3</sup> Let  $F_i^{j \rightarrow k}$  denote the amount lent by bank  $j$  to bank  $k$  on loan  $i$  then:

$$LPI_{L,B,t} = \frac{\sum_{i \in t} F_i^{L \rightarrow B}}{\sum_{i \in t} F_i^{L \rightarrow \text{all}}} \quad (1)$$

where  $t$  denotes time period. This ratio is more likely to be high if  $L$  relies on  $B$  more than on other banks to lend funds in the market.

<sup>3</sup> We discuss our choice of time period in detail below. Since our data is from January 1997 until August 2001, there are 18 quarters and 2 months. We had the option of dropping the last two months or grouping them into one (smaller) quarter. We chose the second option so as to increase our sample size.



Note. This figure plots, on a given quarter  $q$ , the  $BPI\%$  indices for a given bank  $B$  and all its lenders. The  $BPI\%$  index for bank  $B$  and each borrower  $j$  is equal to the ratio of total funds that bank  $B$  has borrowed from bank  $j$ , as a fraction of the total amount of funds that he has borrowed in the market, during the quarter. Lenders for whom the  $BPI\%$  is zero were omitted from the figure.

Fig. 1. Borrower preference indices for a given bank at a specific quarter.

Similarly, we compute a *borrower preference index* ( $BPI$ ) as the ratio of total funds that  $B$  has borrowed from  $L$  in a given time period, as a fraction of the total amount of funds that  $B$  has borrowed in the market in that same period:

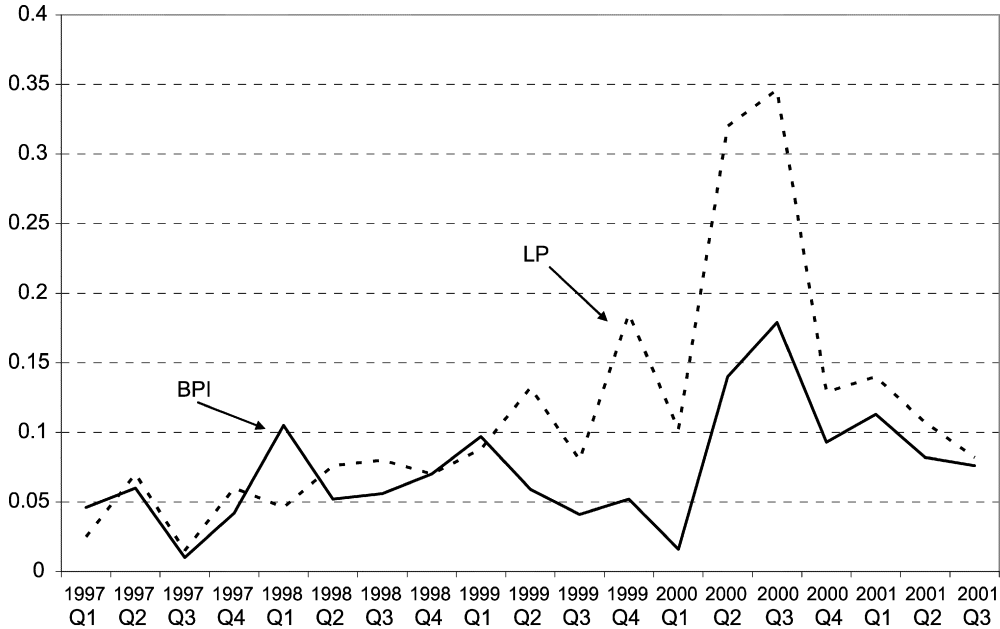
$$BPI_{L,B,t} = \frac{\sum_{i \in t} F_i^{L \rightarrow B}}{\sum_{i \in t} F_i^{\text{any} \rightarrow B}}. \quad (2)$$

Fig. 1 plots, for a given quarter, and for a given borrower, its  $BPI$  indices with different lenders. The most important lender for this borrower during this quarter is the bank labeled as lender one, from whom it borrowed roughly 25% of the total funds that it borrowed during the quarter. This figure illustrates that, in our data, there are asymmetries in financing, with some lenders being much more important than others. As an illustrative example of the time-series dimension of our relationship measures, Fig. 2 plots the evolution of the  $LPI$  and  $BPI$  indices for a pair of banks in our sample,  $L$  and  $B$ . This time-series dimension of our data is also important because it will allow us to deal with the issue of the endogeneity of lending relationships. More precisely, we will be able to use lagged relationship measures as (exogenous) instruments. Fig. 2 also illustrates that there is time variation in our relationship measures. In our regressions the explanatory power comes both from cross-sectional differences across banks, as well as changes over time in bank characteristics.

We have chosen the calendar quarter to measure lending relationships. To some extent this choice is arbitrary. A lending relationship should be fairly stable over time, but not immutable through time. In addition, there is a practical reason to choose the calendar quarter as unit of analysis, since some of our bank data is quarterly, namely information about the banks' assets, profitability and credit risk. In Section 5.5 we show that the results are robust to alternative ways of measuring relationships.

### 2.3. Interest rate measure

In most interbank markets the central bank sets a target rate. For this reason we focus on explaining the difference between the interest rate on a given loan and the average interest rate on overnight loans. We proceed as follows. First for a loan from bank  $L$  to bank  $B$  on day  $d$ , we calculate the difference between the interest rate ( $i_{L,B,d}$ ) and the average (market-wide) overnight interest rate on the



Note. This figure plots the evolution over time of the BPI and LPI indices for a pair of banks in our sample, *B* and *L*. For each quarter, the BPI index is equal to the ratio of total funds that bank *B* has borrowed from bank *L*, as a fraction of the total amount of funds that he has borrowed in the market during the quarter. Similarly, LPI index is equal to the ratio of total funds that bank *L* has lent to bank *B*, as a fraction of the total amount of funds that he has lent in the market, during the quarter.

Fig. 2. Borrower's preference index and lender's preference index for a pair of banks.

same day ( $\bar{i}_d$ ), divided by the standard deviation of overnight interest rates for that day ( $\sigma_d^i$ ). This is to account for the well-documented GARCH effects in interbank market interest rates (Hamilton, 1996). Since our unit of observation is year/quarter, we then obtain the average interest rate difference for all loans from bank *L* to bank *B* during time period *t*, with  $t = 1, \dots, 19$ , as:

$$i_{L,B}^t = \frac{1}{T_t} \sum_{d \in t} (i_{L,B,d} - \bar{i}_d) / \sigma_d^i \tag{3}$$

where  $T_t$  denotes the number of trading days in period *t*.<sup>4</sup>

It is important to note that the average market-wide interest rate shown in (3) is the endogenous result of the market-wide bank relationships that exist. Therefore, one can not interpret it as a measure of the market-wide interest rate that would prevail if there were no relationships. Our paper allows us to address the question of whether banks that use relationships to borrow (lend) do so at rates that are higher (lower) than the average market-wide interest rate, conditional on the average level of relationships that exist in the market. In other words, our analysis allows us to identify the value of using a relationship in a given loan, but conditional on the average level of relationships that exist in the market. If all loans in the market were carried out in the absence of relationships

<sup>4</sup> The exact formula is slightly more complicated, since we must account for the possibility of more than one loan between the same pair of banks on a given day. If we let index *j* denote different loans between the same pair of banks on a given day, the exact formula is:

$$i_{B,L}^t = \frac{1}{T_t} \sum_{d \in t} \frac{1}{J_{L,B,d}} \sum_j (i_{L,B,d,j} - \bar{i}_d) / \sigma_d^i$$

where  $J_{L,B,d}$  denotes the number of loans from *L* to *B* on day *d*.

the market-wide interest rate would change and our results are not informative about what would happen.

#### 2.4. Other variables

In this section we describe the variables that we use to explain the interest rate and lending relationships. The first set of variables that we include are bank size (measured by total assets), quarterly return on assets, and the proportion of non-performing loans (NPL). The latter is defined as loans that are past-due for a period exceeding 90 days, over the total outstanding credit granted by the bank. Several papers have shown that these variables matter for the pricing of Fed Fund loans (Allen and Saunders, 1986; Furfine, 2001, among others). These variables may also constitute important determinants of relationships. Several papers in the interbank market literature model agency problems that arise from asymmetric information between borrowers and lenders of funds, which monitoring may help to overcome (Rochet and Tirole, 1996).<sup>5</sup> The asymmetries of information may be larger, and monitoring may be more important when banks are smaller, profitability is lower, or credit risk (as measured by the proportion of non-performing loans) is higher. It is conceivable that this monitoring also takes place outside of the interbank market. After all, banks undertake many kinds of transactions with each other, of which interbank overnight loans are just one. In Section 5 we construct a measure of interactions between banks that take place outside of the interbank market, to explore this possibility further.

Banks face liquidity risk that arises from the behavior of retail depositors (Ho and Saunders, 1985; Bhattacharya and Gale, 1987; and Freixas et al., 2000). Lending relationships may help banks to insure against such liquidity risk. For example, the model of Carlin et al. (2007) predicts that relationships allow traders who have suffered a liquidity shock (the distressed traders) to transact at more favorable prices. In order to test this prediction we need to obtain a measure of distress. A natural measure can be constructed from the fact that banks are required to satisfy minimum reserve requirements. Over a given reserve maintenance period (or settlement period) a given bank's average reserves must not fall below a given proportion of its short-term liabilities (mostly customer deposits).<sup>6</sup>

If relationships allow banks which have suffered a liquidity shock to transact at more favorable prices, we would expect that, banks' who have a higher shortage of funds in their reserve account, would borrow funds from banks with whom they have a relationship, and through this pay a lower interest rate than they would otherwise. To investigate this prediction we construct a proxy for each bank's reserve requirements, equal to the average of the daily deposits in the bank's reserve account over the reserve maintenance period. We then measure *surplus deposits* for bank  $i$  on day  $d$  ( $SD_{id}$ ) as the ratio between the current average level of deposits in the reserve account (since the start of the current reserve requirement period) and our proxy for reserve requirements.<sup>7</sup> We calculate the average value of this variable over each time period, for those days in which the bank intervened in the interbank market.

To investigate further the extent to which bank relationships provide insurance against liquidity risk, we construct a measure of such risk. First, we measure liquidity shocks by the daily change in the bank's reserve deposits, that is not due to interbank market loans. For each bank and year/quarter, liquidity risk is measured by the standard deviation of liquidity shocks, divided by the bank's average

<sup>5</sup> Broecker (1990), Flannery (1996), and Freixas and Holthausen (2005) also solve models of the interbank market with asymmetric information and credit risk. Freixas and Holthausen (2005) solve such a model in an international setting, when cross-country information is noisy.

<sup>6</sup> Campbell (1987), Hamilton (1996), Hartmann et al. (2001), and Spindt and Hoffmeister (1988) have noticed how shortages of liquidity at the end of the maintenance period often lead to special behavior of overnight rates during those days.

<sup>7</sup> The formula for surplus deposits is:

$$SD_{id} = \frac{\sum_{s \in \{m(d): s \leq d\}} Deposit_{is} / n_d}{\sum_{s \in m(d)} Deposit_{is} / n} \quad (4)$$

where  $m(d)$  refers to the days in the same reserve maintenance period as day  $d$ , and  $n_d$  and  $n$  are the up to  $d$  and the total number of days in the maintenance period, respectively.

**Table 1**  
Summary statistics

Variable	Mean	Stdev	Median	25th perc.	75th perc.
<i>Interbank market</i>					
Market amount (million Euros)	27,123	8545	27,888	24,250	29,444
Market number of loans (million Euros)	2217	994	2478	1412	3032
Number of borrowers	37.19	4.75	39	34	41
Number of lenders	39.31	4.48	40	35	43
<i>Borrower characteristics</i>					
Assets (million Euros)	5736	9372	1850	695	6150
ROA (percent)	17.4	154.3	21.4	5.1	43.7
Non-performing loans (percent)	4.63	8.21	2.68	1.35	5.01
Amount (million Euros)	751	1080	331	44	984
Number of loans	61	71	32	8	95
Surplus deposits	1.00	0.18	1.00	0.93	1.07
Coef. variation shocks	0.77	0.96	0.35	0.11	1.01
<i>Lender characteristics</i>					
Assets (million Euros)	5168	8864	1334	619	4967
ROA (percent)	13.6	163.2	22.0	5.1	45.4
Non-performing loans (percent)	5.47	11.71	2.62	1.16	5.05
Amount (million Euros)	712	1048	419	166	817
Number of loans	58	57	46	20	76
Surplus deposits	1.04	0.17	1.03	0.97	1.10
Coef. variation shocks	0.34	0.43	0.15	0.04	0.41
<i>Borrower/lender characteristics</i>					
Borrower preference index: BPI (percent)	7.94	14.50	3.07	1.25	7.79
Lender preference index: LPI (percent)	8.39	13.30	4.09	1.54	9.71
Correlation of shocks (percent)	11.98	17.31	12.36	1.62	23.6

Notes. This table reports summary statistics for overnight loans and main characteristics of borrowers and lenders in the Portuguese Interbank market. The sample period is January 1997 to August 2001. The variables are defined in [Appendix A](#).

reserves (we denote this variable by CV). We expect banks that face more liquidity risk to rely more on relationships. An important parameter in [Allen and Gale's 2000](#) model is the correlation of liquidity shocks between banks that are related. When this correlation is lower, it implies that when borrowing banks need funds lending banks are more likely to have a surplus of funds. [Allen and Gale \(2000\)](#) show that the larger this correlation is, the more fragile is the financial system. Therefore, we calculate the correlation between each two banks' liquidity shocks, and we use this variable to explain the determinants of relationships (we denote this variable  $\theta_{L,B}$ , where  $L$  and  $B$  identify the borrower and lender).

## 2.5. Summary statistics

[Table 1](#) reports summary statistics. The first panel shows information on the Portuguese interbank market. The average total amount lent in each quarter is 27,123 million euros, with an average 2217 loans. Thus, the average loan amount is roughly twelve million euros. The average number of different borrowers (lenders) in each quarter is 37 (39).

The next two panels of [Table 1](#) report summary statistics for borrowing and lending banks. On average borrowing banks are larger (as measured by total assets), have a higher ROA, and a smaller proportion of NPL than lending banks. This is consistent with borrowing banks having better investment opportunities than lending banks, which explains why they show up as borrowers in the market. [Table 1](#) also reports information on the total amount and the number of loans made and received by each bank in the interbank market during the quarter. On average each bor-

rower receives 751 million Euros in 61 loans, while each lender loans out 712 million Euros in 58 loans.<sup>8</sup>

Table 1's last panel shows summary statistics for the relationship metrics, and for the correlation of shocks. The average *BPI* is 7.94 percent, and the average *LPI* is 8.39 percent. These averages are significantly higher than the median values (3 and 4 percent respectively), a sign of a skewed distribution. That is, banks borrow/lend relatively little from most banks, but large amounts from a few of them.

Our interest rate measure is the difference between the loan interest rate and the average overnight interest rate, so that on average it is zero. But some numbers are helpful for understanding interest rate cross-sectional variability in our sample. The standard deviation of interest rates on a given day is on average 8 basis points. Moreover, this is naturally a strongly skewed distribution. While the median standard deviation is 6 basis points, in ten percent of the days the standard deviation of interest rates is higher than 18 basis points. We have calculated several summary statistics that allow us to understand by how much the interest rate vary across lenders/borrowers. On average the interest rate is 43 basis points higher for small than for large borrowers, and it is 39 basis points higher for large than for small lenders (small (large) are those banks in the bottom (top) one-third of the total assets distribution).<sup>9</sup> Interest rates also tend to vary with return on assets: on average the interest rate is 17 basis points higher for borrowers with a low return on assets (bottom one third) than with a high return on assets (top one third).

### 3. Pricing of interbank loans

#### 3.1. Baseline regressions

We investigate the determinants of the interest rate on interbank market loans. We do so using a regression analysis. An alternative approach would have been to use a matching methodology, in which we would matched banks according to size and other bank characteristics. The matching approach could offer some advantages relative to regression analysis, in that we might have a more appropriate choice for the benchmark interest rate. However, we have decided to use regression analysis since it has several advantages relative to the matching methodology. First, it allows us to simultaneously establish different benchmarks depending on multiple bank characteristics (e.g. bank size, percentage of non-performing loans, profitability), without significantly decreasing cell size, which would happen if we performed matches along several bank characteristics. Second, it allows us to estimate the impact of different bank characteristics (size, profitability, etc.) on the loan interest rate, within the context of a single regression.

We first estimate the unconditional correlation between the relationship metrics and the loan interest rate defined in Section 2.3:

$$i_{L,B}^t = \alpha + \gamma BPI_{L,B}^t + \kappa LPI_{L,B}^t + \beta^t D^t + u_{L,B}^t \quad (5)$$

where  $t$  indexes time,  $D^t$  are time dummies, the subscripts  $L$  and  $B$  refer to lending and borrowing bank, respectively, and  $u_{L,B}^t$  is the residual. Column (i) of Table 2 shows the estimation results. These results appear to suggest that borrowers (lenders) tend to pay (receive) higher (lower) interest rates on loans with banks with whom they have higher relationship indices. We will show that the reason for this result is that the decision of whether to rely on lending relationships is endogenous, and correlated with bank characteristics that also affect the interest rate on the loan. With this in mind we include size, ROA and NPL as additional independent variables. The regression that we estimate is then:

$$i_{L,B}^t = \alpha + \sum_{j=L,B} [\beta_{1j} Size_j^t + \beta_{2j} ROA_j^t + \beta_{3j} NPL_j^t] + \gamma BPI_{L,B}^t + \kappa LPI_{L,B}^t + \beta^t D^t + u_{L,B}^t \quad (6)$$

<sup>8</sup> The average amount and number of loans for borrowing and lending banks are not exactly equal because there is a different number of borrowing and lending banks in the market.

<sup>9</sup> These numbers are very similar to the ones reported by Furfine (2001) for the FED Funds Market.

**Table 2**  
Multivariate model for interest rate

Independent variables	(i)	(ii)	(iii)	(iv)	(v)	(vi) Fixed effects
<i>Borrower characteristics</i>						
Log assets		-0.098*** (13.43)	-0.103*** (12.98)		-0.086*** (8.72)	-0.096*** (3.96)
Market share				-2.141*** (9.80)	-0.603*** (2.25)	
ROA		1.194* (1.84)	1.245* (1.85)	-0.318 (0.48)	-0.032 (1.65)	1.166 (0.04)
Non-performing loans		0.512*** (2.67)	0.548*** (2.72)	0.616*** (3.12)	0.539*** (2.70)	-0.005 (0.02)
Surplus deposits			-0.117** (2.21)	-0.100* (1.85)	-0.111** (2.09)	-0.259*** (4.19)
Coef. variation			0.000 (0.26)	0.000 (0.30)	0.000 (0.04)	-0.001 (0.55)
<i>Lender characteristics</i>						
Log assets		0.083*** (15.25)	0.087*** (14.98)		0.090*** (13.02)	0.112*** (4.89)
Market share				1.666*** (8.29)	-0.129 (0.56)	
ROA		0.150 (0.54)	0.1333 (0.44)	1.184*** (3.69)	0.146 (0.47)	-0.304 (0.74)
Non-performing loans		0.066* (1.66)	0.089 (1.45)	-0.076 (1.19)	0.089 (1.44)	-0.094 (0.78)
Surplus deposits			0.063 (1.18)	0.052 (0.95)	0.059 (1.11)	0.059 (0.97)
Coef. variation			-0.017*** (10.53)	-0.012*** (3.89)	-0.018*** (9.61)	-0.019*** (8.92)
<i>Borrower/lender characteristics</i>						
Correlation of shocks			-0.003 (0.06)	-0.003 (0.05)	-0.004 (0.09)	-0.013 (0.26)
Borrower pref. index	0.240*** (4.18)	-0.155*** (2.71)	-0.184*** (2.85)	-0.142*** (2.00)	-0.196*** (2.83)	-0.253*** (3.60)
Lender pref. index	-0.180*** (3.15)	0.218*** (3.44)	0.347*** (4.78)	0.445*** (5.25)	0.404*** (4.97)	0.331*** (4.44)
Number obs.	7724	7046	6410	6410	6410	6410
R <sup>2</sup>	0.01	0.08	0.08	0.05	0.08	0.11

Notes. The dependent variable is interest rate defined for every pair of lender and borrower as the quarterly average of the difference between the interest rate on the loans between those two banks and the market interest rate on the same days, divided by the standard deviation of interest rates for the day. The independent variables are defined in Appendix A, and they include time fixed effects. Column (vi) shows the estimation results including bank fixed effects in addition to the time fixed effects. The sample period is January 1997 to August 2001. Robust *t*-statistics are shown in parenthesis.

\* Significance at the 10% level.

\*\* Idem, 5%.

\*\*\* Idem, 1%.

As a size measure we use the logarithm of total assets. Column (ii) of Table 2 shows the estimation results. Interestingly, when we include the logarithm of total assets, ROA, and NPL as independent variables, the estimated coefficients on the relationship variables revert sign. Thus lenders receive higher interest rates on loans to borrowers with whom they have a lending relationship, and borrowers pay lower interest rates on loans from banks with whom they have a lending relationship. This result is the opposite of the unconditional results. The estimated coefficients change signs since the relationship measures are correlated with these bank characteristics that also affect the loan interest rate.

The signs of the estimated coefficients of the size variables, positive for lenders and negative for borrowers, show that in the market larger banks receive better interest rates, whichever side of the market they are in. This is consistent with the evidence for the Fed Funds market (Allen and Saunders,

1986; Stigum, 1990; Furfine, 2001). The estimated positive coefficient on the ROA of borrowers is intuitive: borrowers with a higher ROA have a more profitable application for the funds, and thus are willing to pay a higher interest rate for borrowing them. As expected we find that borrowers with a higher proportion of NPL tend to pay higher interest rates on interbank market loans, a result which is statistically significant at the one percent level. The estimated coefficients on ROA and NPL of lenders are not statistically significant, at least when we include as independent variables those that capture liquidity risk (column (iii)). The equation that we estimate is now:

$$i_{L,B}^t = \alpha + \sum_{j=L,B} [\beta_{1j}Size_j^t + \beta_{2j}ROA_j^t + \beta_{3j}NPL_j^t + \beta_{4j}SD_j^t + \beta_{5j}CV_j^t] + \beta_6\theta_{L,B} + \gamma BPI_{L,B}^t + \kappa LPI_{L,B}^t + \beta^t D^t + u_{L,B}^t \quad (7)$$

where *SD* denotes surplus deposits, or the net reserve position of borrowers and lenders when they borrow or lend funds in the market, *CV* denotes the coefficient of variation of liquidity shocks, and  $\theta_{L,B}$  denotes the correlation of liquidity shocks between lender and borrower of funds.

The results in column (iii) of Table 2 show that borrowers with a lower surplus deposit pay on average a higher interest rate on their loans. The magnitude of the coefficient is economically significant: an increase in the shortage of funds from the 25th to the 75th percentile leads to a 13 basis point increase in the loan interest rate. However, if this change is accompanied by an increase in the *BPI* index from the 25th to the 75th percentile, then the increase in the interest rate is only 7 basis points. Thus relationships seem to allow borrowers with a larger reserve imbalance to transact at more favorable rates. The estimated coefficient on the surplus deposits of lenders is not statistically significant. What seems to matter for lenders is the volatility of liquidity shocks: the larger the volatility the lower is the interest rate that lenders receive on interbank market loans. The estimated coefficient on  $\theta_{L,B}$  is not significantly different from zero.

In columns (iv) and (v) we investigate why larger banks receive better rates. The fact that borrowers' size matters is intuitive and could be due to better information being available for larger banks, or to larger banks being too-big-to-fail. However, the reason why larger lenders receive better rates is less clear. A possible explanation may be that larger banks have more bargaining power (Osborne and Rubinstein, 1994). In order to investigate this explanation, we have calculated market shares for borrowers and lenders. Market shares are positively correlated with bank size, as measured by the logarithm of total assets, with coefficients of correlation equal to 0.59 (0.74) for lenders (borrowers). When we include market shares as explanatory variables for the loan interest rate we find that lenders/borrowers with larger market shares receive better rates (column (iv)). When in column (v) we include both market shares and the logarithm of total assets as independent variables we find that the explanatory power of both variables is diminished, reflecting the fact that they are co-linear.

One may be concerned that our results on the impact of the relationship measures on interest rates are driven by unobserved bank heterogeneity. In order to address this concern, the last column of Table 2 shows the estimation results when we include bank fixed effects among the set of explanatory variables. Comparing these results with those in column (iii) of the same table, two conclusions can be drawn. First, some of the variables that we use to capture the effects of borrower characteristics on the loan interest rate are no longer significant. This tells us that these variables were previously significant due to cross sectional differences in bank characteristics, which are now captured by the fixed effects. Second, and importantly, we find that the effects of the relationship measures on the loan interest rate are robust to the introduction of bank fixed effects. More precisely, the estimated coefficients on the *BPI* and *LPI* indices are still negative and positive, respectively, and statistically significant.

It is important to clarify that we do not find that small banks that lend funds in the interbank charge higher interest rates. In fact, we find exactly the opposite. The estimated positive coefficients on log assets for lender characteristics in the second panel of Table 2 shows that larger (smaller) banks receive a higher (lower) interest rate when lending funds in the market. These results hold across all specifications. Therefore we find that: (i) small banks are net lenders in the market but, within all lenders, small banks receive lower interest rates than large banks on the funds that they lend; (ii) large banks are net borrowers in the market but, within all borrowers, large banks pay lower

interest rates than small banks on the funds that they borrow. With respect to lending relationships, the results in Table 2 show that, both smaller and larger banks receive better terms both when borrowing and when lending (pay a lower interest rate when borrowing and receive a higher interest rate when lending) when they interact with banks with whom they have high relationship indices.

### 3.2. Instrumental variables

In order to address the issue of the endogeneity of relationships we estimate Eq. (7) using instrumental variables (IV). This allows us to identify the causal link between the relationship measures and the loan interest rate. This is a departure from most of the existing literature on lending relationships, which does not address the endogeneity of those relationships. The validity of the IV approach depends crucially on the quality of the instruments used in the first stage regression. Good instruments include those which are simultaneously pre-determined and highly correlated with the relationship metrics. Therefore, we explore the time-series dimension of our data set, and use the lagged relationship measures as instruments. Obviously, such instruments are not available in cross sectional data, which is typically used in the existing literature on lending relationships. The quality of these instruments can be measured by the  $R$ -squared of the first-stage regressions: for the *BPI* (*LPI*) measure it is equal to 67% (78%).<sup>10</sup>

The estimation results for the second stage regressions are shown in the column (i) of Table 3. The  $t$ -statistics (reported below the estimated coefficients) have been adjusted for first-stage estimation error. We compare the results in column (i) of Table 3 to those in column (iii) of Table 2, in which we did not use instruments for the relationship metrics. First, the coefficients on total assets and non-performing loans remain essentially unchanged. Second, the estimated coefficient on the surplus deposit of borrowers is no longer significant, and the estimated coefficient on the coefficient of variation of lenders is only significant in (ii). Thus the level of significance of the insurance variables is reduced once we control for the endogeneity of relationships. This suggests that relationships are important because they allow banks to obtain insurance in the interbank market. In the next section we will explicitly study the determinants of lending relationships.

Third, the estimated coefficients on the relationship variables are significant throughout, and have the same signs. Moreover, the magnitude of the estimated coefficients is either unchanged or even slightly increased (in absolute value). This result implies that, at least in our dataset, the endogeneity problem does not affect the inference regarding the causal link between lending relationships and interest rates. Of course, one should be careful about generalizing this result to other applications, since we have only shown that it holds in our data. Furthermore, and even though the estimated coefficients on the relationship metrics are robust to an IV approach, the inference on the coefficients of some of the insurance variables changes. If these are only control variables, then this is not an issue. However, if one is interested in the economic interpretation of those coefficients, then controlling for endogeneity is important.

In column (ii) of Table 3 we report the results of estimating Eq. (7) using instrumental variables, but including bank fixed effects among the set of explanatory variables. As it was the case in Table 2, we see that the effects of the relationship metrics on the loan interest rate are robust to the inclusion of bank fixed effects.

The use of lagged relationship indices as instruments raises some concerns in the presence of measurement error. In that case, even though the true dependent variable and consequently the residual of a hypothetical “true regression” would only be measurable at time  $t$ , the observed value of dependent variable would have a component that is measurable at time  $t - 1$ . This would create serial correlation in the regression residual and lead to inconsistent estimators. However, our data is unlikely to be affected by measurement error in any significant way: we observe the variables directly from central bank data, including the terms of the loan which must be reported separately by borrower and lender to the central bank, which in turn is responsible for the settlement of the loan.

<sup>10</sup> We have also estimated the IV regressions using the first lag of all the explanatory variables in Eq. (7) as instruments in the first-stage regression. The first stage  $R^2$  was almost unaffected, and the second stage results were the same and are therefore not reported.

**Table 3**  
Multivariate model for interest rate: instrumental variables

Independent variables	(i) IV	(ii) IV fixed effects	(iii) Arellano–Bond
<i>Borrower characteristics</i>			
Log assets	−0.103*** (10.16)	−0.112*** (3.89)	0.102 (0.99)
ROA	1.166 (0.95)	−1.011 (0.76)	−1.747 (0.60)
Non-performing loans	0.421** (2.12)	−0.739 (0.27)	−0.358 (0.67)
Surplus deposits	−0.075 (0.98)	−0.253*** (3.13)	−0.171 (1.54)
Coef. variation	−0.011 (0.70)	−0.007 (0.45)	−0.019 (0.49)
<i>Lender characteristics</i>			
Log assets	0.085*** (11.89)	0.113*** (3.99)	0.012 (0.12)
ROA	−0.032 (0.05)	−1.022 (1.29)	−1.806 (1.20)
Non-performing loans	0.095 (0.86)	0.047 (0.24)	−0.011 (0.04)
Surplus deposits	−0.041 (0.54)	0.002 (0.02)	0.317*** (2.78)
Coef. variation	−0.013 (0.32)	−0.034 (0.80)	−0.097 (1.62)
<i>Borrower/lender characteristics</i>			
Correlation of shocks	−0.016 (0.25)	−0.016 (0.24)	−0.071 (0.90)
Borrower pref. index	−0.208* (1.77)	−0.514*** (2.79)	−0.355* (1.90)
Lender pref. index	0.515*** (2.72)	0.777*** (3.41)	0.514*** (2.94)
Lagged bor. pref. index			−0.466* (1.90)
Lagged lend. pref. index			0.571*** (2.34)
Lagged dependent variable			−0.099*** (4.18)
Number obs.	4358	4358	3102
R <sup>2</sup>	0.07	0.11	

*Notes.* The dependent variable is interest rate defined for every pair of lender and borrower as the quarterly average of the difference between the interest rate on the loans between those two banks and the market interest rate on the same days, divided by the standard deviation of interest rates for the day. The independent variables are defined in Appendix A, and they include time fixed effects. Column (i) shows the estimation results for instrumental variables regressions. We use  $BPI_{L,B}^{t-1}$  and  $LPI_{L,B}^{t-1}$  as instruments for  $BPI_{L,B}^t$  and  $LPI_{L,B}^t$ , respectively. Column (ii) shows the estimation results for instrumental variables regressions in which we include bank fixed effects among the set of explanatory variables. Column (iii) shows the estimation results using the Arellano–Bond (1991) dynamic panel data estimator. The lagged borrower and lender preference indices are treated as predetermined variables. The sample period is January 1997 to August 2001. Robust *t*-statistics are shown in parenthesis.

\* Significance at the 10% level.

\*\* Idem, 5%.

\*\*\* Idem, 1%.

In spite of the fact that our data is unlikely to be affected by measurement error, we use the Arellano and Bond (1991) dynamic panel data estimator to investigate the effects of the relationship variables on the loan interest rate. The estimation results are shown in column (iii) of Table 3. These results show that the effects of the relationship indices on the loan interest rate, negative for borrowers and positive for lenders, are robust to the use of the Arellano–Bond estimator.

#### 4. The determinants of lending relationships

The instrumental variables regressions that we have estimated in the previous section allow us to estimate the effects of lending relationships on the loan interest rate, but they do not explain the determinants of lending relationships. In this section we investigate which bank characteristics explain the decision of whether or not to rely on lending relationships. We do so in a setting in which we allow both the loan amount and interest rate to be correlated with the identity of the borrowing and lending banks (i.e. on whether they have a lending relationship). More precisely, we estimate a seemingly unrelated regressions (SUR) system of equations, with the amount lent, interest rate, and the relationship measures between lender and borrower (*LPI* and *BPI*) as our endogenous dependent variables. Thus, we estimate *simultaneously* the following equations:

$$i_{L,B}^t = \alpha^1 + \sum_{j=L,B} [\beta_{1j}^1 \text{Size}_j^t + \beta_{2j}^1 \text{ROA}_j^t + \beta_{3j}^1 \text{NPL}_j^t + \beta_{4j}^1 \text{SD}_j^t + \beta_{5j}^1 \text{CV}_j^t] + \beta_6^1 \theta_{B,L} + \beta^{t1} D^{t1} + u_{L,B}^t, \quad (8)$$

$$\text{BPI}_{L,B}^t = \alpha^2 + \sum_{j=L,B} [\beta_{1j}^2 \text{Size}_j^t + \beta_{2j}^2 \text{ROA}_j^t + \beta_{3j}^2 \text{NPL}_j^t + \beta_{4j}^2 \text{SD}_j^t + \beta_{5j}^2 \text{CV}_j^t] + \beta_6^2 \theta_{B,L} + \beta^{t2} D^{t2} + \varepsilon_{L,B}^t, \quad (9)$$

$$\text{LPI}_{L,B}^t = \alpha^3 + \sum_{j=L,B} [\beta_{1j}^3 \text{Size}_j^t + \beta_{2j}^3 \text{ROA}_j^t + \beta_{3j}^3 \text{NPL}_j^t + \beta_{4j}^3 \text{SD}_j^t + \beta_{5j}^3 \text{CV}_j^t] + \beta_6^3 \theta_{B,L} + \beta^{t3} D^{t3} + \xi_{L,B}^t, \quad (10)$$

$$\text{Ln}(V_{L,B}^t) = \alpha^4 + \sum_{j=L,B} [\beta_{1j}^4 \text{Size}_j^t + \beta_{2j}^4 \text{ROA}_j^t + \beta_{3j}^4 \text{NPL}_j^t + \beta_{4j}^4 \text{SD}_j^t + \beta_{5j}^4 \text{CV}_j^t] + \beta_6^4 \theta_{B,L} + \beta^{t4} D^{t4} + v_{L,B}^t, \quad (11)$$

where  $V_{L,B}^t$  is the total amount of funds lent by bank *L* to bank *B* during time period *t*, and *Ln* denotes logarithm. We estimate a reduced form system, and therefore allow for contemporaneous correlation across the four different innovations (*u*,  $\varepsilon$ ,  $\xi$  and *v*). We include time dummies in all equations.

##### 4.1. *BPI* and *LPI* equations

Table 4 shows the estimation results. The results for the *BPI* equation are shown in the second column. In this equation we try to determine which borrower and lender characteristics explain the variation in *BPI* indices. In other words, who are the borrowers who have higher relationship indices, and who are the lenders with whom they have those higher indices. For instance, the negative estimated coefficient on the logarithm of total assets of borrowers shows that small borrowers rely more on lending relationships. On the other hand, the estimated positive coefficient on the total assets of lenders in the same equation, implies that small borrowers tend to have large banks as their preferred lenders. These results suggest a dichotomy between large and small banks in the market, an issue that we explore further in Section 5.1.

Interestingly, we find that borrowers with higher default risk are more likely to rely on lending relationships (the estimated coefficient on *NPL* in the *BPI* equation is positive) and to pay higher interest rates (the estimated coefficient on *NPL* in the interest rate equation is also positive). From these two results one may reasonably expect that banks which borrow funds from banks with whom they have a lending relationship pay higher rates. This may seem inconsistent with the result in Table 2 that loan rates tend to be lower for banks borrowing from lenders with whom they have large relationship indices.

The key to understanding this apparent inconsistency is to note that in Table 2 we did not find that unconditionally borrowers with a high default risk and large *BPI* indices pay lower interest rates. In fact the reverse is true: large values for *BPI* indices tend to be associated with higher interest

**Table 4**  
SUR model

Independent variables	<i>BPI</i>	<i>LPI</i>	Int. rate	Amount
	<i>Borrower</i>			
Log assets	−0.025 <sup>***</sup> (20.67)	0.024 <sup>***</sup> (23.14)	−0.090 <sup>***</sup> (13.40)	6.313 <sup>***</sup> (7.33)
ROA	0.088 (0.49)	−0.064 (0.42)	1.207 (1.22)	−178.190 (1.41)
Non-performing loans	0.152 <sup>***</sup> (5.47)	−0.009 (0.36)	0.517 <sup>***</sup> (3.32)	−34.552 <sup>*</sup> (1.74)
Surplus deposit	−0.044 <sup>***</sup> (3.71)	−0.051 <sup>***</sup> (5.05)	−0.143 <sup>**</sup> (2.17)	23.017 <sup>***</sup> (2.75)
Coef. variation	0.011 <sup>***</sup> (16.03)	−0.000 (0.40)	−0.002 (0.47)	−0.776 (1.63)
	<i>Lender</i>			
Log assets	0.011 <sup>***</sup> (10.33)	−0.001 (1.43)	0.084 <sup>***</sup> (14.37)	−5.442 <sup>***</sup> (7.27)
ROA	−0.025 (0.23)	−0.064 (0.69)	0.116 (0.19)	−337.062 <sup>***</sup> (4.40)
Non-performing loans	0.003 (0.19)	−0.003 (0.18)	0.087 (0.89)	44.831 <sup>***</sup> (3.55)
Surplus deposit	−0.009 (0.77)	−0.001 (0.14)	0.064 (0.98)	−24.495 <sup>***</sup> (2.92)
Coef. variation	−0.002 <sup>**</sup> (2.20)	0.015 <sup>***</sup> (18.45)	−0.012 <sup>**</sup> (2.26)	−1.423 <sup>**</sup> (2.14)
	<i>Borrower/lender</i>			
Correlation of shocks	−0.062 <sup>***</sup> (6.37)	−0.049 <sup>**</sup> (5.85)	−0.008 (0.16)	−64.583 <sup>***</sup> (9.31)
Number obs.	6410	6410	6410	6410
<i>R</i> <sup>2</sup>	0.17	0.19	0.08	0.05
	<i>Correlation of residuals</i>			
<i>BPI</i>	1.000			
<i>LPI</i>	0.128	1.000		
Interest rate	−0.026	0.049	1.000	
Amount	0.312	0.438	0.008	1.000

Notes. We estimate a SUR system where the dependent variables are the interest rate, the borrower and lender preference indices, and the logarithm of loan volume. The independent variables are defined in Appendix A, and they include time fixed effects. The sample period is January 1997 to August 2001. Robust *t*-statistics are shown in parenthesis.

\* Significance at the 10% level.

\*\* Idem, 5%.

\*\*\* Idem, 1%.

rates (column (i) in Table 2). It is only when controlling for the proportion of *NPL* that the estimated coefficient on the *BPI* index becomes negative (Table 2 column (ii)), but even then it is an order of magnitude smaller than the coefficient on the default risk variable. That is: borrowers with a high proportion of *NPL* pay on average higher interest rates, but the interest rate premium is smaller if they borrow funds from a lender with whom they have a high *BPI*.

Some calculations help to clarify this important point. Consider an increase in the proportion of *NPL* from the 25th to the 75th percentile, while everything else remains the same. Using the estimated coefficients in the third column of Table 2 we see that the interest rate on the loan increases by 2 basis points.<sup>11</sup> However, if the increase in the proportion of *NPL* is accompanied by an increase in the *BPI* index from the 25th to the 75th percentile, the interest rate only goes up by 0.6 basis points. If instead we consider an increase in the proportion of *NPL* from the 10th to the 90th percentile the

<sup>11</sup> Due to our scaling of the dependent variable we need to multiply this increase by the standard deviation of the interest rate.

interest rate now goes up by 20 basis points when the *BPI* index is unchanged, and by 5 basis points when the *BPI* index also increases from the 10th to the 90th percentile.<sup>12</sup>

The fact that borrowers with a higher proportion of *NPL* rely more on relationships suggests banks relationships may help overcome agency problems. One could reasonably question where does the monitoring associated with such relationships take place. After all, repeated overnight loans are frequent, but lenders are only able to observe the extent to which borrowers were able to repay the loan. It is conceivable that the monitoring associated with these relationships also takes place outside of the interbank market, as banks undertake many kinds of transactions with each other. In Section 5 we construct a measure of bank interactions that take place outside of the interbank market, to explore this issue further.

Interestingly we also find evidence that relationships allow banks to insure against liquidity risk. More precisely, we find that banks with a larger imbalance in their reserve deposits are more likely to borrow funds from banks with whom they have a relationship (the estimated coefficient on surplus deposits in the *BPI* equation is negative). This result supports the prediction of Carlin et al.'s (2007) model that under repeated interaction cooperation among traders is an equilibrium outcome which involves refraining from predation, and that allows distressed traders to access liquidity. In addition, we find that borrowers with more volatile liquidity shocks tend to rely more on lending relationships (the coefficient on  $CV_B$  is positive), and they tend to do so with lenders that have less volatile liquidity shocks (the estimated coefficient on  $CV_L$  in the *BPI* equation is negative). This result lends further support to the idea that relationships allow banks to insure against liquidity risk.

The third column of Table 4 reports the results for the *LPI* equation. Similarly to the borrowers, we find that small lenders tend to have larger relationship indices with large borrowers (the estimated coefficient on total assets of lenders is negative and on the total assets of borrowers is positive). In addition, lenders with more volatile liquidity shocks tend to have higher relationship indices with borrowers that face less volatile liquidity shocks, although the estimated coefficient for borrowers is not significantly different from zero.

The estimated coefficients on the correlation of liquidity shocks are negative in both the *BPI* and *LPI* equations. Banks are more likely to have high relationship indices with banks with whom their liquidity shocks are less correlated. This is an interesting and important finding since Allen and Gale (2000) show that the financial system is less fragile when the correlation of liquidity shocks between banks that are related is lower. This may further enhance market liquidity.

As a whole, columns two and three of Table 4 show that it is mostly borrower characteristics that explain variation in the relationship indices. One might have an a priori expectation that for non-secure loans such as interbank market loans, borrowers' characteristics are more important for explaining the terms of the loan than lenders' characteristics. Table 4 suggests that this reasoning carries through when explaining lending relationships.

#### 4.2. Interest rate and loan volume equations

The fourth column of Table 4 shows the results for the interest rate equation. This equation is similar to that estimated in specification (iii) of Table 2, except that now we do not include the *LPI* and *BPI* indices as independent variables, but instead treat them as endogenous when estimating the system of equations. The results are similar to those reported in Table 2. In the last column of Table 4 we report the results for loan volume (the fourth equation in the SUR system). We find that larger banks borrow larger amounts. Interestingly, we find that more profitable banks lend less (the estimated coefficients on  $ROA_L$  is negative). In addition, we find that banks with a higher proportion of non-performing loans lend more and borrow less. The estimated coefficients for *ROA* and *NPL* are consistent with banks that have better investment opportunities borrowing more and lending less. Finally, the estimated coefficients on surplus deposit show that banks which have smaller imbalances tend to rely on larger loans with any particular bank.

<sup>12</sup> The full effect of *NPL* on the interest rate may be even larger because default risk is likely to be correlated with bank size, for which we are also controlling in Table 2.

At the bottom of Table 4 we report the estimated correlation matrix of residuals in the system of equations. Larger residuals for the *BPI* (*LPI*) equation are associated with lower (higher) interest rates, but these correlations are fairly small. The largest correlations are of amount lent with *LPI* and *BPI*, which are equal to 0.44 and 0.31, respectively. This supports the idea that relationships have the greatest effect on the provision of credit, and not on the price at which banks are able to borrow or lend.

## 5. Further evidence on the determinants of lending relationships

In this section we provide further evidence on the determinants of lending relationships, that allows us to be more precise as to their exact nature.<sup>13</sup>

### 5.1. Small versus large banks

The estimation results in the previous sections show that bank size is an important determinant of interbank market interest rates, and of lending relationships. In this section we explore further the role of bank size in the market structure. In order to do so, and for each time period in our sample, we classify banks into large and small, based on the distribution of bank assets. Large (small) banks are those whose assets are larger (smaller) than percentile 66 (33) of this distribution. We then compare several variables for small and large banks.

The first two rows of Table 5, Panel A report the average amount borrowed/lent per bank and period over the whole sample period. The third row reports the net amount borrowed, which is simply the difference between the first two. The second column shows the results for all banks, i.e. not conditional on bank size, while columns three and four show the results for small and large banks, respectively. On average, and per period, each bank in our sample has lent/borrowed 596.5 million euros. There are significant differences between small and large banks: large banks tend to be net borrowers, with the average net amount borrowed roughly equal to 400 million euros, while small banks tend to be net lenders, with the average net amount lent equal to 363 million euros.

Interestingly, this pattern of trade, in which large banks tend to be net buyers of liquidity and small banks tend to be net sellers, is also a distinctive feature of the U.S. Fed Funds market (Furfine, 1999; Ho and Saunders, 1985).<sup>14</sup> It can be rationalized by the model of Ho and Saunders (1985). If large banks are better able to diversify their risk exposure than small banks, then larger banks will be more rate sensitive than small banks, and the slopes of the demand functions for interbank funds of large banks will be more price-elastic than those of small banks.

Table 5, Panel A reports information on the number of loans and the average loan amount. Large (small) banks tend to transact mostly as borrowers (lenders), reflecting the fact that they tend to be net borrowers (lenders) in the market. Unsurprisingly, the average loan amount for small banks is significantly lower than the average loan amount for large banks. The last three rows of Table 5, Panel A report the proportion of non-performing loans, and relationship indices. Small banks tend to have a significantly higher proportion of non-performing loans than large banks. Furthermore, they tend to have significantly higher *BPI* indices than large banks when borrowing funds. This suggests that small banks find it optimal, when borrowing funds, to concentrate their borrowing activity. Interestingly, the same is not true when lending funds, since there are no statistically significant differences in *LPI* indices between small and large banks.

We have also investigate the likelihood that banks appear on both sides of the market, i.e. as lenders and borrowers, over a given time period. Panel B of Table 5 reports that 66.1% (50.2%) of all banks have been on average active market participants on both sides of the market at least once a month (week).

Panel B of Table 5 also reports summary statistics for bank assets and proportion of non-performing loans as a function of how often banks appear on both sides of the market. It shows

<sup>13</sup> We would like to thank an anonymous referee for suggestions that have led us to investigate the questions in this section.

<sup>14</sup> See also Stigum's (1990) description of the Fed Funds market: "To cultivate correspondents that will sell funds to them, large banks stand ready to buy whatever sums these banks offer, whether they need all these funds or not."

Table 5

Panel A: Small versus large banks				
Variable	All	Small (S)	Large (L)	<i>p</i> -value $S = L$
Total amount borrowed (million Euros)	596.50	124.18	923.87	0.000
Total amount lent (million Euros)	596.50	487.44	524.18	0.643
Net amount borrowed (million Euros)	0.00	−363.26	399.69	0.000
# Loans as borrower	48.77	21.02	62.59	0.000
# Loans as lender	48.77	66.91	35.24	0.000
# Loans as borrower – # Loans as lender	0.00	−45.89	27.35	0.000
Average loan size as borrower	12.23	5.91	14.76	0.000
Average loan size as lender	12.23	7.29	14.87	0.000
Non-performing loans (percent)	5.33	8.74	3.72	0.000
Borrower preference index ( <i>BPI</i> )	9.13	15.22	6.85	0.000
Lender preference index ( <i>LPI</i> )	9.65	10.13	12.06	0.148
Panel B: Frequency of borrowing and lending positions				
Frequency on both sides of the market	Proportion of banks	Bank assets (million of euros)	Non-performing loans	
At least once a month	66.1%	6058	5.53%	
At least once every two weeks	61.3%	6395	4.72%	
At least once a week	50.2%	7271	4.42%	
At least twice a week	38.7%	8420	4.20%	

Notes to Panel A: Large (small) banks are those in the top (bottom) one third of the bank assets distribution. The division between large and small is made on a quarterly basis, using the respective total assets distribution. The table reports averages across the sample. The variables are defined in Appendix A. The last column shows the *p*-value of a *t*-test of equality of the values for small and large banks.

Notes to Panel B: This table shows the proportion of banks that appear on both sides of the market, i.e. as lenders and borrowers, over a given time period. The last two columns report average bank assets and non-performing loans for banks that appear on both sides of the market over the corresponding time period.

that large banks are more likely to appear on both sides of the market, and in this way act as intermediaries. In addition, banks that reverse their positions more frequently tend to have a significantly lower proportion of non-performing loans. Naturally, banks with lower credit risk are better-suited to act as intermediaries. Finally, we have investigated whether the volatility of liquidity shocks differs depending on the frequency with which banks appear on both sides of the market, but found no statistically significant differences.

Smaller banks are less likely to act as intermediaries, and are more likely to act as lenders. But is it the case that when they need to borrow funds they do so from the banks to whom they usually lend funds? In order to investigate this we have estimated the probability that small banks borrow funds from a bank to whom they usually lend funds, where the latter means a bank in top fifty percent (one third) of the distribution of *LPI* indices for that small bank. This probability is as high as 66.88% (54.58% for the one-third cutoff). The corresponding probabilities for all banks, i.e. not conditional on bank size, are smaller and equal to 59.28% (48.43%). Thus small banks, when reversing roles, tend to rely more on banks with whom they usually interact on the other side of the market than the average bank in our sample.

## 5.2. International linkages

In order to explore international linkages between domestic and foreign banks, we have obtained data from a different dataset, namely from the Trans-European Automated Real-time Gross settlement Express Transfer system (TARGET). This is the real-time gross settlement system for the euro offered by the Eurosystem. It is mainly used for the settlement of large-value euro interbank transfers. This dataset contains information on the identity of both the sender and receiver of funds, and on the amount transferred. It has some shortcomings. First, transfers of funds between a pair of banks may be due to a variety of reasons, other than interbank loans. For example, if a large individual client of a foreign bank decides to transfer funds to a domestic bank, this transfer of funds will show up in

**Table 6**  
International linkages

	Banks with low access	Banks with high access	<i>p</i> -value of test eq. means
Total assets (million Euros)	1940.74	9645.24	0.000
Non-performing loans (percent)	8.22	2.50	0.003
Coef. variation shocks	0.555	0.493	0.802
Borrower preference index ( <i>BPI</i> )	18.41	9.25	0.000
Lender preference index ( <i>LPI</i> )	13.60	12.64	0.644
Total amount borrowed (million Euros)	115.35	925.15	0.000
Total amount lent (million Euros)	592.52	538.36	0.711
# Loans as borrower	13.99	51.67	0.000
# Loans as lender	52.36	23.46	0.000

*Notes.* The measure of access to international markets is funds that the bank has sent abroad plus received from abroad during the quarter divided by bank's assets. Banks with low (high) access to international markets are those in the bottom (top) one third of the distribution. The table reports averages for these two groups from 1999 onwards, the sample period for which we have international data. The last column shows the *p*-value of a *t*-test of equality of the values for banks with low and high access.

the dataset, and cannot be distinguished from an interbank loan. Second, this dataset is only available from 1999 onwards, or roughly the second half of the sample period.

We use this dataset to investigate how international linkages relate to the nature of lending relationships in the domestic interbank market. This is particularly interesting because the Euro area seems to be characterized by a two-tier structure, in which only large banks are usually able to access foreign interbank markets for liquidity, and in which small banks tend to do their interbank business through large domestic banks (European Central Bank, January 2000). With this in mind, we first construct a measure of access to international markets, by calculating the total amount of funds that each domestic bank has received from plus sent abroad during each quarter. We then scale this variable by bank size, as measured by the total bank assets.<sup>15</sup>

We think that this variable is a better measure of access to international markets, than simply the difference between funds received from abroad and funds sent abroad scaled by bank assets. This is because a domestic bank may find it easy to access international interbank markets, but during a given time period it may neither be net borrower nor net lender in these markets. In this case the latter variable would be zero. We classify banks into having low and high access to international markets, according to this measure. Banks with high (low) access are those in the top (bottom) one third of the distribution of this variable. Table 6 shows the results for the mean of several variables for each of these two groups. The last column shows the *p*-value for a *t*-test of equality of means.

The first row confirms the result that banks with better access to international markets tend to be larger: the difference in total bank assets between the two groups is almost five-fold. Interestingly, we find that banks with low access to international markets tend to have a much higher proportion of non-performing loans. Furthermore, these banks, when borrowing funds in the domestic interbank market, find it optimal to concentrate their loans: their *BPI* indices are much higher than those with high access to international market. This result is consistent with peer monitoring across borders being less efficient than at the domestic level, as in the model of Freixas and Holthausen (2005). It suggests that in international unsecured credit markets, such as interbank markets, peer monitoring plays an important role in that it allows liquidity to flow across borders. However, an alternative explanation is that large banks are perceived by international markets as being too-big-too-fail, and for this reason they can borrow internationally at low rates. In either case, our results suggest that domestic regulators should direct their policies towards an improvement of the cross-border information available, particularly so on small banks, so as to enhance cross-border market integration.

<sup>15</sup> We have also calculated alternative measures of access to international markets. We have considered both the total amount of funds that each domestic bank has received from abroad during the quarter scaled by bank assets, and the total amount of funds that each domestic bank has sent abroad during the quarter scaled by bank assets. The correlation coefficient between these two variables is 0.97, and the correlation coefficients between them and the total amount of funds sent plus received from abroad scaled by bank assets are over 0.99.

Finally, we find that banks with high access to international markets tend to have a lower coefficient of variation of liquidity shocks, but the difference relative to banks with low access to international markets is not statistically significant.

### 5.3. Interactions outside of the interbank market

Banks undertake many kinds of transactions with each other, of which interbank overnight loans are only one. Other types of transactions include intra-day debits on payment systems, the trading of contingent claims such as interest rate and exchange rate derivatives in over-the-counter markets, among others. These transactions differ in their frequency and the degree to which they offer an opportunity for banks to establish relationships. In order to better understand the economic role of relationships, it is important that we measure these other interactions that take place between banks (the previously defined relationship variables measure interactions in the interbank market).

For this purpose, we have obtained data on the financial flows that take place between each pair of banks. We subtract the flows that are the result of interbank market loans. One can think of these other financial flows as a measure of the interactions between banks outside of the interbank market. First, and for each time period and pair of banks, we calculate the total amount of the flows between them (funds received plus funds sent). We then scale the total amount of these flows by the total assets of each of the banks, to obtain measures of other relationships for both borrower and lender of funds. These measures are positively correlated with the *BPI* and *LPI* indices, with coefficients of correlation equal to 0.41 and 0.31, respectively.

We include the measures of other relationships in the SUR regression analysis. Table 7 shows the estimation results. We find that the measures of other relationships are strongly positively correlated with the *BPI* and *LPI* indices (their estimated coefficients, reported in the second and third columns of Table 7, are highly significant). Thus, interbank market relationships do seem to be part of wider relationships between banks. This is confirmed in the loan amount equation, where we observe that banks with stronger outside relationships trade larger loan amounts with each other in the interbank market. However, when comparing the results in Tables 4 and 7, we find that the estimated coefficients for the control variables are essentially unaffected by the inclusion of the other relationships measures. In the interest rate regression we find that borrowers (lenders) with stronger outside relationship measures tend to pay a lower (receive a higher) interest rate in interbank market loans, but the estimated coefficients are not statistically significant.

### 5.4. Time-series probabilities of repeated interactions

In order to better understand the time-series dimension of the relationship between borrowers and lenders we estimate the probability of repeated interbank market loans. More precisely, we estimate the probability that a given lender (*L*) will lend funds to a given borrower (*B*) in the next *k* days, that is from  $d + 1$  to  $d + k$ , conditional on *L* having lent funds to *B* at *d*, and conditional on both *L* and *B* lending and borrowing funds in the market in the next *k* days. Thus, we are trying to answer the following question: given that *B* has borrowed from *L* at *d*, and given that *B* needs funds again sometime within the next *k* trading days, how likely is it that it will borrow from *L* again?

Before we turn to the estimation results let us first calculate what we should expect to observe if the matching mechanism was completely random. The average number of loans on a given day is 43.31, and the average daily number of active lenders in the market is 23.1. This corresponds to the average of 1.87 loans per lender each day. Since the average daily number of active borrowers is 17.95, if the matching was completely random the probability of a lender lending to the same borrower at  $d + 1$ , conditional on having done so at *d* and on both lender and borrower being active in the market at  $d + 1$ , is 10.2%.<sup>16</sup> This probability is roughly one fifth of the value that we have estimated in the

<sup>16</sup> With probability  $1/17.95$  the bank lends to the same borrower in its first loan, plus with probability  $(1-1/17.95)$  it does not lend to the same borrower in the first loan, but it does so with probability  $0.87/17.95$  in the 0.87 remaining loan, so that the probability is  $1/17.95 + (1 - 1/17.95) \times 0.87/17.95$ .

**Table 7**  
SUR model including other relationships measure

Independent variables	BPI	LPI	Int. rate	Amount
<i>Borrower</i>				
Log assets	−0.0158*** (11.74)	0.027*** (22.45)	−0.092*** (−11.20)	8.924*** (8.74)
ROA	0.0047 (0.16)	0.002 (0.01)	2.228 (1.22)	−631.190*** (−2.80)
Non-performing loans	0.116*** (2.74)	−0.040 (−1.05)	0.752*** (2.91)	−56.276* (1.76)
Surplus deposit	−0.045*** (−3.73)	−0.049*** (−4.56)	−0.193** (2.60)	29.609*** (3.23)
Coef. variation	0.010*** (15.20)	−0.001** (−2.13)	−0.001 (−0.28)	−0.557 (−1.16)
<i>Lender</i>				
Log assets	0.005*** (4.43)	−0.005 (−5.43)	0.084*** (12.22)	−7.149*** (−8.42)
ROA	0.140 (1.18)	0.193 (1.64)	−0.026 (−0.04)	−36.205*** (−0.40)
Non-performing loans	0.006 (0.34)	0.002 (0.15)	0.078 (0.68)	54.349*** (3.86)
Surplus deposit	−0.014 (−1.17)	−0.010 (−0.97)	0.069 (0.07)	−31.865*** (−3.52)
Coef. variation	−0.012*** (−4.09)	0.075*** (27.64)	−0.007 (0.37)	−10.942** (−4.75)
<i>Borrower/lender</i>				
Correlation of shocks	−0.051*** (−5.06)	−0.058*** (−6.42)	−0.012 (0.19)	−65.534*** (−8.51)
Other relationships borrower	1.117*** (24.29)	3.178*** (7.80)	−1.678 (−0.60)	3.730** (10.83)
Other relationships lender	3.623*** (10.07)	6.662*** (4.20)	2.458 (1.00)	7.530** (29.65)
Number obs.	6410	6410	6410	6410
R <sup>2</sup>	0.27	0.26	0.07	0.08
<i>Correlation of residuals</i>				
BPI	1.000			
LPI	0.130	1.000		
Interest rate	−0.012	0.050	1.000	
Amount	0.304	0.465	0.017	1.000

Notes. We estimate a SUR system where the dependent variables are the interest rate, borrower and lender preference indices, and the logarithm of loan volume. The independent variables are defined in the appendix and they include time fixed effects. The sample period is January 1997 to August 2001. Robust *t*-statistics are shown in parenthesis.

\* Significance at the 10% level.

\*\* Idem, 5%.

\*\*\* Idem, 1%.

data, and equal to 51% (Table 8, Panel A). This probability increases to 64% if we consider *k* equal to five, and if we take a 30-day window the probability is as high as 87%. These probabilities are much larger than those we would obtain with a random matching mechanism, which are 18% and 51% for a five and a thirty-day window, respectively. The differences are statistically significant at the 1% significance level. Thus, in the interbank market, lenders frequently use previous borrowers and vice-versa, and much more frequently than one would obtain if the matching mechanism was random.

With our previous analysis of bank size in mind, in Panel B of Table 8 we take this analysis in that direction. In particular we estimate and find that the probability of repeated interaction is higher if one of the banks is small (asset size below percentile 33) and the other one is large (asset size above percentile 66). When both the borrower and the lender are large the probability of repeated

**Table 8**

Probability of repeated interactions assuming random matching and in the data

Panel A: Random matching and in the data for all banks			
Number of days	Random matching	Data	p-value: random = data
1	0.102	0.511	0.000
3	0.140	0.585	0.000
5	0.179	0.643	0.000
10	0.269	0.732	0.000
30	0.513	0.865	0.000
Panel B: In the data by bank size			
Number of days	Large–large (LL)	Large–small (LS)	Small–small (SS)
1	0.526 LS**	0.547 LL**	0.333
3	0.591 SS**	0.590 SS**	0.355 LL**, LS**
5	0.653 LS**, SS***	0.671 LL**, SS***	0.429 LL***, LS***
10	0.741 LS***, SS***	0.779 LL***, SS***	0.447 LL***, LS***
30	0.875 LS***, SS***	0.904 LL***, SS***	0.581 LL***, LS***

Notes. This table shows the probability that a given lender ( $L$ ) will lend funds to a given borrower ( $B$ ) in the next  $k$  days, that is from  $d + 1$  to  $d + k$ , conditional on  $L$  having lent funds to  $B$  at  $t$ , and conditional on both  $L$  and  $B$  lending and borrowing funds in the market in the next  $k$  trading days. The table shows the results for  $k = 1, 3, 5, 10, 30$ . Panel A shows the calculated probability assuming random matching of lenders and borrowers, and the estimated probabilities in the data. The last column of Panel A shows the  $p$ -value of a test of the equality of the random matching probabilities and the estimated probabilities in the data. Panel B shows the estimated probabilities in the data by bank size. Large (small) banks are those in the top (bottom) one third of the distribution of total assets. Below the estimated coefficients we report whether the estimated probabilities are statistically significant across banks of different sizes.

\*\* Significance at the 5% level.

\*\*\* Idem, 1%.

interaction is lower, and it is lowest when both lender and borrower are small. These estimated probabilities suggest that lending relationships are most important when between small and large banks in the domestic market. In Panel B of Table 8, below the estimated probabilities, we report whether these probabilities are statistically different from one another. It is important to note that for  $k$  equal to one we do not find that the probability of SS is significantly different than LL or LS because there are very few observations for SS and  $k = 1$ .

### 5.5. Robustness checks

We have investigated the robustness of our results to alternative relationship measures. More precisely, we have also constructed lender and borrower preference indices using number of loans instead of loan amounts. That is the lender preference index was constructed as the number of times that  $L$  has lent funds to  $B$  during time period  $t$ , as a fraction of the total number of times that bank  $L$  has lent funds in the interbank market during the time period. The results were similar to the baseline results and are not reported.

We have also used as alternative measures of lending relationships the (absolute) number of different banks to which bank  $L$  lent funds during time period  $t$ , and the number of different banks from which bank  $B$  borrowed funds during  $t$ . The main difference in terms of the results was that in the interest rate regression the borrower preference index thus measured is not significant. Thus it seems that for borrowers of funds it is important to use as a measure of the strength of the relationship a variable that reflects the (possible) asymmetric nature of the financing.

We have constructed  $LPI$  as being equal to the total amount that bank  $L$  has lent to bank  $B$  as a fraction of the total amount that bank  $L$  has lent in the interbank market during the period. However,

during the same period bank  $L$  may borrow funds from bank  $B$ . We have investigated the robustness of the results to measures that take into account a two-sided relationship factor, with the borrower preference index defined as the total amount bank  $B$  borrowed from plus lent to bank  $L$  divided by the total amount of funds that  $B$  has borrowed plus lent in the market during period  $t$ . The estimation results for these alternative relationship measures are similar to those we obtained before (and are not reported).

## 6. Conclusion and policy implications

Interbank markets play an important role in distributing liquidity across the financial system. It is in this market that banks obtain insurance against idiosyncratic liquidity shocks arising from the behavior of retail depositors, by borrowing and lending funds among themselves (as in the models of Ho and Saunders, 1985; Bhattacharya and Gale, 1987; and Freixas et al., 2000). The bilateral nature of the market allows banks to establish relationships. In this paper we have studied the role of bank relationships in the process of liquidity provision in the interbank market.

We have constructed measures of interbank market relationships, based on the intensity of banks' pair-wise lending activity. We have found that banks with a larger imbalance in their reserve deposits are more likely to borrow funds from banks with whom they have a relationship, and to pay a lower interest rate on these loans than they would otherwise. This result supports the prediction of Carlin et al.'s (2007) model that under repeated interaction cooperation among traders is an equilibrium outcome that involves refraining from predation, and that allows distressed traders, or banks with a larger imbalance in their reserve deposits, to transact at more favorable prices.

We have found evidence that smaller banks and banks with a larger proportion of non-performing loans tend to rely more on lending relationships when borrowing funds in the domestic market. This is consistent with relationships allowing banks to access liquidity in the presence of market frictions such as transaction and information costs.

In order to be more precise as to the exact nature of lending relationships, we have investigated the role of bank size in the market structure. Interestingly, we have documented that large banks tend to be net buyers of liquidity and small banks tend to be net sellers. This pattern of trade is also a distinctive feature of the U.S. Fed Funds market (Furfine, 1999; Ho and Saunders, 1985), and it can be rationalized by the model of Ho and Saunders (1985). If large banks are better able to diversify their risk exposure than small banks, then large banks will be more sensitive to interest rates than small banks, and the slopes of the demand functions for interbank funds of large banks will be more price-elastic than those of small banks.

We have also investigated how access to international markets affects the nature of lending relationships in the domestic market. We have documented that large domestic banks tend to have better access to international markets. Interestingly, banks with low access to international markets tend to have a much higher proportion of non-performing loans. Furthermore, these banks, when borrowing in the domestic interbank market, find it optimal to concentrate their loans. This result is consistent with peer monitoring across borders being less efficient than at the domestic level, as in the model of Freixas and Holthausen (2005). It suggests that in international unsecured credit markets such as interbank markets, peer monitoring plays an important role in that it allows liquidity to flow across borders. However, an alternative explanation is that large banks are perceived by international markets as being too-big-too-fail, and for this reason they can borrow internationally. In either case, our results suggest that domestic regulators should direct their policies towards an improvement of the cross-border information available, particularly so on small banks, so as to enhance cross-border market integration.

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## Appendix A. Definition of the variables

### A.1. Market wide variables

*Market amount*: total volume of overnight loans during the quarter in millions of Euros

*Market number of loans*: total number of overnight loans during the quarter

*Number of borrowers (lenders)*: number of borrowing (lending) banks during the quarter

### A.2. Bank variables

*Assets*: bank assets at the beginning of the quarter (in millions of Euros)

*ROA*: annualized quarterly return on assets (in percentage terms)

*Non-performing loans*: loans that are overdue for more than 90 days divided by the total value of outstanding loans

*Amount*: total amount of overnight loans during the quarter (in millions of Euros)

*Market share*: total amount that the bank has lent (borrowed) in the interbank market during the quarter over the total market volume

*Net amount borrowed*: total amount borrowed minus total amount lent

*Number of loans*: number of overnight loans during the quarter

*Surplus deposits*: quarterly average of the ratio between the current level of deposits in the reserve account (average since the start of the current reserve requirement period) and the reserve requirements of that period

*Correlation of shocks*: coefficient of correlation between the daily changes in the central bank deposits (not including the interbank market operations) of lender and borrower

*Coefficient of variation of shocks*: standard deviation of the daily changes in the bank's reserve deposits not due to interbank market loans divided by the bank's quarterly reserves

### A.3. Relationship variables

*BPI (LPI)*: total funds borrowed (lent) from a specific lender (borrower) as a fraction of the total funds that the bank has borrowed (lent) in the market during the period

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