Multiple Banking Relationships and Exposure at Default:

Evidence from the Italian Market

by

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Abstract

Multiple banking relationships represent a signal offered to the market and to other lenders about firm risk; normally, the higher the number of lenders, the lower the risk of the exposure. The literature focuses prevalently on the role of multiple lending in explaining a bank's lending and its probability of the default.

No evidence is provided of the role of multiple lending in explaining exposure at default (EAD), even if in all industrialized economies, due to the existence of credit registers, the amount of lending is also defined on the basis of each debtor's exposure with respect to the financial system. The paper considers a representative and unique Italian banking system database and demonstrates that multiple lending affects EAD and the effect is more significant for default with respect to short-term past dues. Considering the EAD drivers, we find a higher number of lenders positively affects exposure due to the lack of monitoring incentives and the effect is more significant when the role of non-reference banks is weaker

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1. Introduction

Multiple banking relationships are common almost all countries, even if the number of lenders normally used by European borrowers is higher than that used by the Americans (Ongena and Smith, 2000). The standard monitoring theory proposed by Diamond (1984) does not justify this business practice because it implies a duplication of monitoring costs that could be saved if each borrower obtained lending from only one bank.

The literature demonstrates that normally firms that have a lower number of lenders and establish long-term relationships with them collect money at a lower interest rate (Berger and Udell, 1995) and with lower collateral requirements (Boot and Thakor, 1994) due to the decreased opaqueness and borrower risk (Petersen and Rajan, 1994). The choice of multiple lending exposure is normally justified by the risk that superior available information enables a single bank to extract monopoly rents (Sharpe, 1990) and generally firms with greater growing opportunities and more opaque assets are more interested in this choice (Farinha and Santos, 2002).

Analysis of the role of multiple lending in explaining bank risk exposure is still limited and focused prevalently on the probability of default and the loss given default. Regarding the former, there is no consensus in the literature on the impact of multiple lending on the risk drivers: some propose the thesis that the greater the number of lenders, the lower the probability of default will be due to the lack of information monopoly and, therefore, the lower the incentives to finance high-risk projects (Jimenez and Saurina, 2004). Others, however, demonstrate that a longer-term relationship with a prominent bank will ensure the lender's support in managing liquidity problems (Elsas and Krahnen, 1998). For the latter case, the role of collateral is normally higher for transaction lending in the medium and long term, while it is higher for relationship lending in the short term; therefore, the loss given default will be lower in the medium to long term for a single lending relationship and in the short term for multiple lending solutions (Jimenez, Salas, and Saurina, 2006).

The third driver of the expected loss, exposure at default (EAD), is never analysed in a relationship with the role of single or multiple lending exposure, even if credit line usage is affected by banks' monitoring and control activities (Zhao, Dwyer, and Zhang, 2011). The intensity of bank monitoring activity can be influenced by the structure of relationships (Foglia, Laviola, and Marullo Reedtz, 1998) because the private information a financial institution generates about a firm is less valuable when the firm deals with multiple sources of financial services (Cole, 1998).

The paper contributes to the literature considering the impact of multiple lending on EAD, looking at the behaviour of defaulted borrowers with respect to their principal and other lenders. The results show that multiple lending relationships reduce a bank's default exposure and the results are more significant for a past due default definition with respect to restructured credits. The choice of considering the characteristics of a multiple relationship allows an increase in the predictability of EAD and a reduction in the probability of underestimating the risk exposure.

This paper is organized as follows. After presenting a detailed literature review of EAD (Section 2), it summarizes the main characteristics of the sample collected and its representativeness with respect to the overall market (Section 3.1). It then presents the methodology for constructing the EAD proxy and evaluating its determinants (Section 3.2) and discusses the results and main implications (Section 3.3). The last section summarizes the main conclusions.

2. Literature review

Since EAD determines a bank's potential amount of loss when the debtor enters default status, it is a key driver in the calculation of regulatory capital requirements (Basel Committee on Banking Supervision, 2006). A bank's EAD depends on the features of both the debtor and the facility (Basel Committee on Banking Supervision, 2005). The lower the credit rating, the higher the usage of residual credit lines (Asarnow and Marker, 1995), even though better-rated firms tend to convert commitments in cash exposure to a greater extent, showing, on average, higher loan equivalents (LE) (Araten and Jacobs, 2001). Although low cash flow firms have limited access to credit lines (Sufi, 2008), growing firms with access use credit lines very intensively (Agarwal et al., 2004). Credit risk mitigation through collateral determines a higher LE (Jimenez, Lopez, and Saurina, 2009) and the exposure is affected by the collateral types of non-defaulters (Zhao et al. 2011). Since commitments purchased by firms show different levels of complexity (Schockley and Thakor, 1997), EAD differs across different types of products (Araten and Jacobs, 2001) and the predictability of the risk parameter is strictly affected by the relevance of the undrawn amount of the commitment (Asarnow and Marker, 1995). In addition to borrower and facility features, credit line usage is affected by banks' monitoring and control activities (Zhao et al., 2011), since banks have an advantage in offering debt financing services that provide real-time financial information on the borrower (Norden and Weber, 2010). As banks develop relationships with firms, they acquire information that is not shared with other financial intermediaries (Lummer and McConnell, 1989), even though firms borrow for the first time in their life from a single bank but soon afterward may start borrowing from additional banks (Farinha and Santos, 2002).

The structure of banking relationships influences the concentration/parcellization of debtor exposure; consequently, creditors experience a disadvantage in holding a limited and shared set of information to appraise debtor credit risk (Detragiache, Garella, and Guiso, 2000). Multiple banking relationships affect the entering of default status, since a large number of creditors decreases a manager's incentives to default strategically (Bolton and Scharfstein, 1996). Since the intensity of the banking system's monitoring can be influenced by the structure of relationships (Foglia et al., 1998), the controlling actions on debtor exposure to verify each creditor's adherence to the loan covenants can be affected by the exclusiveness/sharing of financial relationships, since the private information a financial institution generates about a firm is less valuable when the firm deals with multiple sources of financial services (Cole, 1998) and, therefore, bank actions can suffer from lack of coordination (Ongena and Smith, 2000). The value of the private information that a bank can obtain from an exclusive relationship increases with the relationship's duration (Petersen and Rajan, 1994). Lending relationships are also affected by the product type: Credit lines tend to be more concentrated at a single bank, while other exposures are more dispersed among different creditors due to their transaction-driven nature (Berger and Udell, 1995). The duration composition of multiple exposures affects debtor credit (He and Xiong, 2012) while, at the single creditor level, shorter maturities can be used to derive an implicit priority rule (Brunnermeier and Oehmke, 2010).

3. Empirical analysis

3.1 Sample

Our sample is a proprietary database provided by the Bank of Italy that collects for each month of the year all exposures that were classified as past due at least once before 2010 for customers who did not have banking facilities offered by more than one bank. The data provider, Centrale dei Rischi, is one of the most complete public databases on business loans worldwide (Jappelli and Pagano, 2003) because it collects credit exposures accounting for more than 30,000 euros for all Italian banks and financial intermediaries (Banca d'Italia, 2010). The dataset for the analysis contains information for the time interval 2006–2010 on the monthly utilization of self-liquidating debt and callable loans by firms featuring multiple credit relationships that entered default status in 2010.

For each counterparty, we collect all the information related to exposure with respect to the Italian banking system since 2006 on a monthly basis and we classify these exposures on the basis of the reporting bank, type of credit, and guarantee (Table 1).

Table 1. Sample description

	Counterparties	Number of contracts	Number of banks for each customer			% Guarantee		% Type	
			Min	Mean	Max	With	Without	Self-liquidating	Callable
December, 2006	77,745	406,789	1	2.92	47	4.54%	95.46%	43.47%	56.53%
December, 2007	86,086	447,427	1	2.94	46	4.57%	95.43%	43.11%	56.89%
December, 2008	91,187	455,008	1	2.88	47	4.87%	95.13%	42.77%	57.23%
December, 2009	107,575	522,242	1	2.95	44	4.77%	95.33%	39.39%	60.61%
December, 2010	96,872	430,099	1	2.76	44	4.86%	95.14%	38.02%	61.98%

Source: Bank of Italy data processed by the authors

For each year the sample includes more than 75,000 counterparties for a number of contracts established to be always higher than 400,000. The average number of banks offering service to each customer is greater than two but varies significantly among firms. In fact, it is always possible each year to find a firm with exposure related to only one bank at least for one month and borrowers that collect money from more than 40 lenders in the same month.

The types of exposures considered are frequently not guaranteed because, in the sample, personal and real guarantees are offered only for less than 5% of the sample.

All the contracts considered can be classified as either self-liquidating exposures or callable loans and, on the basis of the amount of exposure related to each type of contract, the relevance is comparable even if callable solutions are always more relevant (10–20%) than self-liquidating ones.

3.2 Methodology

The EAD measurement considers both the usage ratio and the LE:

$$Usage\ ratio_i = UR_i = \frac{Balance_{i,Default}}{Commitment_{i,Default-t}} \tag{1}$$

$$Loan\ Equivalent_i = LE_i = \frac{Balance_{i,Default} - Balance_{i,Default-t}}{Commitment_{i,Default-t} - Balance_{i,Default-t}} \tag{2}$$

where UR measures the credit line percentage utilization (with respect to the commitment) at the time of default for debtor *i* and represents the ex post exposure of default for the banking system. It is computed by looking at all exposures assumed by each debtor (Jimenez et al., 2009). Following the Basel Committee on Banking Supervision's (2006, para. 414) prescriptions for the rating system time horizon, we consider different time horizons, from one month to one year.

The variable LE measures the portion of a credit line's undrawn commitment that is likely to be drawn down by the borrower in the event of default (Moral, 2006). In light of the prudential regulation (Basel Committee on Banking Supervision, 2006), it represents the exante proxy of EAD risk related to counterparties with the same characteristics as the defaulted debtor. As for the usage ratio, we consider different time horizons, from one month to one year.

To evaluate counterparties without undrawn commitment, as in the case of term loans and self-liquidating debt, the momentum approach is implemented:

$$Momentum_i = MU_i = \frac{Balance_{i,Default}}{Commitment_{i,Default}} \tag{3}$$

where the ratio assumes a value closer to one when the debtor is using the maximum amount of credit available before default (CEBS, 2006).

To overcome the inapplicability of the previous formula in the case of a positive balance without commitment, we also consider the approach of the exposure multiplier:

$$Exposure\ Multiplier_i = EM_i = \frac{Balance_{i,Default}}{Balance_{i,Default-t}} \tag{4}$$

where the analysis is based on the ratio between current exposure at the time of default and exposure registered some months earlier (Resti et al., 2009).

The sample is divided into single and multiple lending relationships to reveal any differences in the EAD proxies for counterparties with one or multiple banking relationships. We also consider separately the different types of defaults (past due 90 days, past due 180 days, and restructured credits).

Following the approach proposed by Valvonis (2008), we try to evaluate the drivers of the EAD proxies, considering the following:

- The borrower's risk features,
- The bank's risk appetite,
- Facility characteristics, and
- Borrowing opportunities offered by other banks.

Regarding borrowing risk, due to the blindness of the data available, the borrowers' risk features we consider are legal status and a proxy for size. For the legal status, we construct a dummy variable for limited liability (LL_i) that assumes a value of one if the customer is a public limited company or a limited partnership and zero otherwise. We expect that limited liability will have a negative impact on EAD due to the higher quality and amount of information available for evaluating exposure (Storey, 1994). For the size proxy, due to the lack of balance sheet data, we consider the natural logarithm of overall commitment ($LnCommitment_i$). We expect larger firms to increase their usage of lines of credits less, even when near to the default (Jimenez et al., 2009).

For bank risk appetite, we consider the legal status of the reference bank, the size of the reference bank, and the percentage of defaults. Special types of banks can be characterized by different monitoring procedures and different information availability (Elsas, 2005) and we consider these differences by using two dummy variables (BCC_i and $Other\ Lender_i$) that assume a value of one if the main lenders is, respectively, a cooperative bank or not a bank. Due to the lack of data, our proxy for bank size is related only to lending activity and measures (the natural logarithm of) outstanding credits ($Main\ lender\ Size_i$). We expect to find a positive relationship with the EAD proxy because the bank has a lower incentive to monitor small exposures properly and normally invests less in collecting soft information from local branches (Agarwal and Hauswald, 2010). A bank's risk appetite is measured as the ratio of the amount of defaulted exposures with respect to the overall lending offered at the end of the year ($Main\ lender\ Risk_i$). We expect higher average risk assumed by a bank to normally lead to higher EAD (Cerasi and Daltung, 2000).

The facility features considered include the role of fewer risk contracts, the role of short-term exposures, and the role of guarantees (Zhao et al., 2011). The role of less risky exposures is measured as the natural logarithm of self-liquidating exposures (AL_i), which represent a safe lending solution for the sample. The role of short-term exposures is constructed by considering a one-year horizon as a threshold and computing the natural logarithm of the short-term exposure

(BT_i). The analysis of the guarantees considers both personal and real ones and our proxy is constructed as the natural logarithm of the overall amount guaranteed for each debtor (Gar_i).

The analysis of the role of multiple lending solutions considers both the number of other lenders used by the firm and the role of the main lender in covering the firm's financial needs (Carletti, Cerasi, and Daltung, 2007). The number of financial intermediaries considers all banks that provide financing opportunities to the firm, independent of the number and size of the financial products offered $(N°\ Banks_i)$. The role of the reference lender is measured as the ratio of the outstanding debt offered by the main financial intermediary with respect to overall market exposure $(\%\ Main\ Bank\ _i)$.

The analysis proposed considers yearly contribution of a different set of explanatory variables in determining the EAD proxy:

$$UR_{i,t} = \alpha + UR_{i,t-1} + \sum_{k=1}^{n} \beta_k Borrower\ Risk_{i,t}^{k} + \sum_{j=1}^{m} \beta_j Lender\ Risk_{i,t}^{j} + \sum_{v=1}^{o} \beta_{v,t} Facility\ Type\ _{i,t}^{v} + \sum_{l=1}^{p} \beta_l Multiple\ Lending_{i,t}^{l}\ + \varepsilon_i \tag{5}$$

$$LE_{i,Year\ t} = \alpha + LE_{i,t-1} + \sum_{k=1}^{n} Borrower\ Risk_{i,t}^{k} + \sum_{j=1}^{m} Lender\ Risk_{i,t}^{j} + \sum_{v=1}^{o} Facility\ Type\ _{i,t}^{v} + \sum_{l=1}^{p} Multiple\ Lending_{i,t}^{l}\ + \varepsilon_i \tag{6}$$

$$MU_{i,Year\ t} = \alpha + MU_{i,t-1} + \sum_{k=1}^{n} Borrower\ Risk_{i,t}^{k} + \sum_{j=1}^{m} Lender\ Risk_{i,t}^{j} + \sum_{v=1}^{o} Facility\ Type\ _{i,t}^{v} + \sum_{l=1}^{p} Multiple\ Lending_{i,t}^{l}\ + \varepsilon_i \tag{7}$$

$$EM_{i,Year\ t} = \alpha + EM_{i,t-1} + \sum_{k=1}^{n} Borrower\ Risk_{i,t}^{k} + \sum_{j=1}^{m} Lender\ Risk_{i,t}^{j} + \sum_{v=1}^{o} Facility\ Type\ _{i,t}^{v} + \sum_{l=1}^{p} Multiple\ Lending_{i,t}^{l}\ + \varepsilon_i \tag{8}$$

All the regressions are presented separately for each year (2006–2010) to test the increasing or decreasing role of the multiple lending relationships in explaining EAD proxy dynamics. Following a standard approach for decomposing the contribution of some explanatory factors of the fitness of the linear model (e.g. Lee and Devaney, 2007), we measure the contribution of the multiple lending variables in increasing the model's statistical fitness (on the basis of R^2).

To evaluate the model's usefulness in predicting the next year's exposure, we also use estimated coefficients at time t - 1 to forecast the EAD proxy at time t. We provide summary statistics about the frequency and types of error (overestimates versus underestimates) related to the different models previously used, given by equations (5) to (8).

3.3 Results

A preliminary analysis of the role of multiple banking relationships in explaining EAD dynamics is carried out considering separately customers with only one bank and those with multiple relationships. Table 2 presents summary statistics for the difference of EAD proxies computed for defaulted and in bonis customers.

Table 2. Comparison of EAD proxies and in bonis exposures for single and multiple banking relationships on the overall time horizon (median value)

EAD Proxy	In bonis customers		Defaulted Customers	
	Single	Multiple	Single	Multiple
UR_{1M}	71.29%	75.24%	98.32%	89.73%
UR_{3M}	64.98%	75.14%	93.23%	88.30%
UR_{6M}	56.72%	75.82%	78.81%	86.02%
UR_{9M}	44.15%	74.16%	58.36%	83.00%
UR_{1Y}	30.95%	72.89%	46.14%	77.65%
LE_{1M}	0.00%	1.57%	0.00%	0.32%
LE_{3M}	0.00%	5.15%	-3.39%	2.05%
LE_{6M}	0.00%	9.40%	0.00%	3.45%
LE_{9M}	0.00%	6.77%	0.00%	0.38%
LE_{12M}	0.00%	4.27%	0.00%	0.00%
MU	100%	91.05%	75.07%	74.61%
EM_{1M}	99.89%	100.19%	100.00%	100.00%
EM_{3M}	94.28%	101.71%	102.42%	101.22%
EM_{6M}	86.38%	102.41%	102.21%	101.62%
EM_{9M}	61.90%	103.04%	91.33%	101.40%
EM_{1Y}	40.29%	100.59%	69.21%	97.61%
Legend: Single = Single Bank Relationship Multiple = Multiple Banking Relationship				

Source: Bank of Italy data processed by the authors

The analysis of the usage ratio (UR) demonstrates that, near to the default (independent of the number of lenders), the usage of lines of credit increases significantly and only near default (not more than three months before) are counterparties with higher numbers of lenders less risky with respect to a single lending relationship. This evidence can be explained in light of the active management policy of non-reference lenders for risky borrowers (Norden and Weber, 2010) to recover their residual exposure before default.

The analysis of the LE demonstrates that multiple banking relationships cause higher variability of the balance of defaults because debtors modify their credit exposure on the basis of the prices and conditions applied by lenders. The results are not affected by the choice of considering in bonis or defaulted counterparties, but the difference is higher (in median value) when in bonis counterparties are taken into account. This evidence suggests that a relationship approach holds (Petersen and Rajan, 1994) that prevents the equal distribution of exposure among the different lenders and that near to default debtors are more financially constrained by lenders (Araten and Jacobs, 2001). Moreover, the data show that the potential cash exposure is better controlled in a single lending relationship, since LE is never positive in all the time horizons selected.

Considering momentum (MU), the usage of lines of credit is higher (in median value) for single lending relationships and for in bonis exposure. If we take defaulted customers into account, multiple banking relationships are characterized by the lower usage of credit lines, suggesting the unavaibility of marginal banks to support the risky customers due to the incomplete information set. However, the difference is not huge as for in bonis customers, suggesting the relevance of other features (Foglia et al. 1998). For in bonis customers, MU is much higher for single relationships, implying that performing firms are allowed to access more external funds when the information is more concentrated due to a stricter relationship with one lender (Carletti et al., 2007).

Looking at the time trend of the balance at default through exposure multiplies (EM), we find that multiple banking relationships near default (one to six months before) increase less than single banking relationships do. The analysis of the benchmark scenario of in bonis exposures demonstrates that the lower growth rate does not hold, supporting the hypothesis that, in a multiple banking relationship scenario, the probability of increasing bank debt is higher than in a single relations scenario (Marullo-Reedtz, 1994).

The analysis of the EAD is released considering separately customers with a past due of 90 days, those with a past due of 180 days, and customers with restructured debt. The results demonstrate that the multiple banking relationship is more effective in reducing exposure only for some types of credits (Table 3).

Table 3. Comparison of EAD proxies for single and multiple banking relationships for different type of default (median value)

	Past due 90 days		Past due 180 days		Restructured credits	
	DM	%	DM	%	DM	%
UR_{1M}	11.83%	100.00%	-0.92%	100.00%	10.62%	100.00%
UR_{3M}	11.49%	91.36%	-1.74%	91.36%	11.29%	79.70%
UR_{6M}	6.20%	67.58%	-4.89%	67.58%	12.97%	67.58%
UR_{9M}	-8.64%	8.48%	-11.76%	8.48%	11.09%	21.97%
UR_{1Y}	-20.67%	0.00%	-19.90%	0.00%	5.63%	3.33%
LE_{1M}	-1.07%	0.00%	-0.06%	0.00%	0.00%	16.97%
LE_{3M}	-10.93%	0.00%	-5.39%	0.00%	0.58%	32.12%
LE_{6M}	-15.71%	0.00%	-10.56%	0.00%	3.35%	55.76%
LE_{9M}	-21.50%	0.00%	-10.26%	0.00%	4.82%	31.97%
LE_{12M}	0.00%	0.00%	0.00%	0.00%	14.45%	16.67%
MU	12.29%	100.00%	1.36%	100.00%	9.30%	100.00%
EM_{1M}	0.00%	35.45%	0.00%	50.91%	0.00%	59.24%
EM_{3M}	0.89%	49.09%	1.04%	76.21%	-0.09%	38.94%
EM_{6M}	-1.28%	0.00%	1.78%	40.61%	0.99%	38.94%
EM_{9M}	-13.58%	0.00%	-4.04%	0.00%	2.34%	5.00%
EM_{1Y}	-26.54%	0.00%	-9.38%	0.00%	0.60%	0.00%

Legend:
DM = Difference of Median values for single and multiple borrower
% = Percentage of customers with median value higher for single tenant than multiple

Source: Bank of Italy data processed by the authors

The usage ratio (UR) for multiple banking relationships is higher for 90 days past due and restructured credits, while the median value of the exposure for single lender relationships is higher for 180 past due. The results show that, in a scenario of multiple banking relationships, banks are not worried for exposures related to longer defaults (180 days or more) and they do not monitor the usage of the line of credits. Once default occurs and credit is restructured, the data show that lenders of multiple borrowers lose their capability to monitor and reduce exposure. This evidence can be explained in light of default as an absorbing state (Crouhy, Galai, and Mark, 2000) in which all creditors are equal because they share the same information and recovery actions and are prevented from individually realizing debtors' assets (Bolton and Scharfstein, 1996).

Considering the LE, we find multiple lending solutions allow for the reduction of ex ante EAD only for restructured credits, while for those past due, the number of customers with exclusive bank relationships with a lower LE with respect to the multiple bank relationships is insignificant.

The analysis of the momentum (MU) demonstrates that multiple lending relationships always perform better (100%) with respect to a unique banking relationship, independent of the type of default. The positive difference is maximum for past due 90 days and minimum for past due 180 days.

The analysis of the exposure multiplier (EM) shows that the lower exposure related to multiple lending relationships is essentially related to those past due 90 days, while for all other types of default, single lender exposure is lower than the multiple one.

The analysis of the role of multiple lending relationships in explaining the EAD proxy is carried out by considering separately each of the four years analysed and looking only at EAD proxies constructed on a one-year time horizon (Table 4).[1]

Notwithstanding the EAD proxy considered (UR, LE, MU, or EM), the current year value cannot be forecast only on the basis of last year's value. The results support the hypothesis that near default the usage of lines of credit is only incoherent with historical behaviour (Norden and Weber, 2010) and, to predict exposure, other features of the lending relationship must be considered.

The variables related to exposure characteristics do not significantly affect exposure at default and the main drivers are related to lender characteristics. Excluding 2010, more severe lending policies have been adopted by almost all financial intermediaries. Cooperative banks and non-banks always exhibit a higher EAD with respect to average banks. In 2010, the higher EAD is driven by bigger players, while the bank risk proxy seems to do not affect significantly the EAD.

Multiple banking exposure is a driver of the EAD for all the time period: while for the first three years an higher concentration of exposures with respect of the reference bank represents a statistical significant driver of the EAD in the 2010 also the simple decrease of the number for lenders is sufficient in order to increase the EAD.

[1] The results related to the analysis of EAD proxies constructed for smaller time horizons (one month, three months, six months, and nine months) are available in the Appendix. The data for 2006 are dropped because the risk proxy lag of one year cannot be computed.

Table 4. The role of multiple exposures in explaining the Exposure at Default – 1 year time horizon

	UR_t				LE_t			
	2007	2008	2009	2010	2007	2008	2009	2010
$Constant$	-385.75	-78.68	-10.29	16.60	-3.79	-0.79	-0.10	0.16
UR_{t-1}	-0.01	0.00	0.00	-0.00	-	-	-	-
LE_{t-1}	-	-	-	-	-0.01	-0.00	0.00	-0.00
MU_{t-1}	-	-	-	-	-	-	-	-
EM_{t-1}	-	-	-	-	-	-	-	-
$LnCommitment_i$	-0.01	-0.07	-0.01	-0.00	-0.01	-0.07	-0.01	-0.00
LL_i	-0.83	-0.06	-0.03	-4.81	-0.83	-0.06	-0.03	-0.05
BT_{it}	-4.43	-0.46	-0.06	-0.56	-4.44	-0.47	-0.06	-0.56
AL_{it}	4.67	0.59	0.11	0.54	4.77	0.59	0.11	0.54
Gar_{it}	-0.00	-0.00	-0.00	-0.00**	-0.00	-0.00	0.00	0.00
BCC_i	7.94**	1.06**	0.20**	-0.31**	7.93**	1.06**	0.20**	-0.31**
$Other\ Lender_i$	7.02	1.04**	0.16*	-0.33*	7.01	1.04**	0.16*	-0.33**
$Main\ lender\ Size_i$	0.15	0.02	0.00	0.02*	0.15	0.02	0.00	0.02*
$Main\ lender\ Risk_i$	-0.08	0.02	0.04	-0.00	-0.09	0.02	0.04	-0.00
$N°\ Banks_i$	2.74	-0.17	-0.04	-0.20*	-2.74	-0.17	-0.04	-0.20*
$\%\ Main\ Bank\ _i$	0.64*	0.06*	0.01*	0.01*	0.64*	0.06*	0.01*	0.01*
Obs.	8255	11884	23853	24890	8255	11884	23853	24890
R^2	0.15	0.26	0.07	0.10	0.15	0.26	0.07	0.10

Source: Bank of Italy's data processed by the authors

Table 4. The role of multiple exposures in explaining the Exposure at Default – 1 year time horizon (continued)

	MU_t				EM_t			
	2007	2008	2009	2010	2007	2008	2009	2010
$Constant$	-3.79	-0.79	-0.10	0.17	-3.79	-0.79	-0.10	0.17
UR_{t-1}	-	-	-	-	-	-	-	-
LE_{t-1}	-	-	-	-	-	-	-	-
MU_{t-1}	-0.01	-0.01	0.00	-0.00	-	-	-	-
EM_{t-1}	-	-	-	-	-0.01	-0.02	0.00	-0.00
$LnCommitment_i$	-0.82	-0.07	-0.01	-0.00	-0.82	-0.07	-0.01	-0.00
LL_i	-0.83	-0.06	-0.03	-0.05	-0.83	-0.06	-0.03	-0.05
BT_{it}	-4.43	-0.47	-0.06	-0.56	-4.43	-0.47	-0.06	-0.56
AL_{it}	4.68	0.59	0.11	0.54	4.68	0.59	0.11	0.54
Gar_{it}	-0.00	-0.00	0.00	-0.00	-0.00	-0.00	0.00	-0.00
BCC_i	7.93^{**}	1.07^{**}	0.20^{**}	-0.31^{**}	7.93^{**}	1.07^{**}	0.20^{**}	-0.31^{**}
$Other\ Lender_i$	7.01	1.05^{**}	0.16^{*}	-0.33^{**}	7.01	1.04^{**}	0.16^{*}	-0.33^{**}
$Main\ lender\ Size_i$	0.15	0.02	0.00	0.02^{*}	0.15	0.02	0.00	0.02^{*}
$Main\ lender\ Risk_i$	-0.09	0.02	0.04	-0.02	-0.09	0.02	0.04	-0.22
$N°\ Banks_i$	2.74	-0.17	-0.03	-0.20^{*}	2.73	-0.17	-0.04	-0.20^{*}
$\%\ Main\ Bank\ _i$	0.65^{*}	0.07^{**}	0.01^{*}	0.01^{*}	0.65^{*}	0.07^{**}	0.01^{*}	0.01^{*}
Obs.	8255	11884	23853	24890	8255	11884	23853	24890
R^2	0.15	0.26	0.07	0.10	0.15	0.26	0.07	0.10

Source: Bank of Italy's data processed by the authors

To verify the contribution of multiple lending exposures in determining EAD, we consider both the contribution of multiple lending exposures to the R^2 of the previous regression analysis and the contribution to the risk of overestimation or underestimation of EAD (Table 5).

Table 5. Forecasting model and the role of the multiple lending proxies – 1 year time horizon

EAD Proxy	Year	Without Multiple Lending proxies			With Multiple Lending proxies		
		R^2	% UP	$\frac{\sum UP}{\sum\lvert UP\rvert + \sum\lvert Down\rvert}$	R^2	% UP	$\frac{\sum UP}{\sum\lvert UP\rvert + \sum\lvert Down\rvert}$
UR_t	2007	0.12	61.15%	1.14	0.15	58.60%	1.11
	2008	0.20	59.05%	1.02	0.26	53.94%	1.10
	2009	0.06	63.23%	1.07	0.07	61.44%	1.25
	2010	0.09	48.49%	0.99	0.10	46.37%	1.07
LE_t	2007	0.12	61.12%	1.15	0.15	58.58%	1.11
	2008	0.20	59.05%	1.02	0.26	53.95%	1.10
	2009	0.06	63.26%	1.06	0.07	61.45%	1.25
	2010	0.09	48.49%	0.99	0.10	46.37%	1.07
MU_t	2007	0.12	61.12%	1.15	0.15	58.58%	1.11
	2008	0.20	59.05%	1.03	0.26	53.95%	1.03
	2009	0.06	63.26%	1.10	0.07	61.45%	1.06
	2010	0.09	48.49%	1.26	0.10	46.37%	0.99
EM_t	2007	0.12	58.19%	1.07	0.15	58.08%	1.11
	2008	0.20	59.05%	1.02	0.26	53.95%	1.10
	2009	0.06	61.45%	1.02	0.07	59.05%	1.26
	2010	0.09	48.49%	0.99	0.10	46.37%	1.07

Notes:

$\%UP$ = Percentage of overestimates

$\frac{\sum UP}{\sum\lvert UP\rvert + \sum\lvert Down\rvert}$ = Sum of overestimates with respect to the overall overestimates and underestimates (in absolute value)

Source: Bank of Italy's data processed by the authors

Forecasting models show greater statistical fitness (measured by the R^2) when multiple lending proxies are taken into account and EAD estimates are more frequently overestimated than for models constructed without multiple lending exposures. The choice to include multiple lending proxies therefore not only increases the model's statistical fitness, but also decreases the risk assumed by the lender due to the fact EAD is more frequently overestimated. The analysis of the ratio between the size of the overestimations and the overall deviations from expected values does not clearly show the benefits related to also using the multiple lending exposure proxies, since both are significantly affected by outliers.

4. Conclusions

Multiple lending can affect bank exposure in the event of default and an analysis of the ex ante and ex post proxies demonstrates that the existence of multiple lenders leads to a lower monitoring for short period past dues, while when the past due is longer and/or credit is restructured, the existence of multiple lenders increases the efficiency of the monitoring process and reduces the amount of exposure in the event of default. All other things being equal, the ex ante EAD proxies are less affected by multiple lending with respect to ex post lending, demonstrating that the existence of multiple lenders does not reduce the risk assumed and can only reduce the loss sustained due to the information provided to the market by other banks' behaviour.

The analysis proposed measures the EAD for different types of lenders and demonstrates that the existence of multiple relationships can significantly affect the EAD measured with different proxies Moreover, the paper provides evidence that the type of lender and the relevance of the main bank in financing the debtor contribute to explain EAD variability, while last year EAD proxies are not significant. This results are critical in light of the capital adequacy regulation that requires the estimation of the one year EAD starting from the current balance sheet value.

Multiple lending proxies are useful in predicting the next year's EAD and to reduce the risk for the lender of overestimating the risk proxy, by alleviating the credit rationing problem when financing firms.

Further detailed analysis of multiple banking relationship features (e.g. vintage of the relationship, concentration of exposures) can provide further insight into lenders to select the best debtors on the basis of existing exposure with other intermediaries. A more detailed analysis of the drivers of EAD before the default occurs can allow one to identify if multiple lending proxies are important for both in bonis and defaulted exposures.

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Table A.1. The role of multiple exposures in explaining the Exposure at Default – 1 month time horizon

	UR_t				LE_t				EM_t			
	2007	2008	2009	2010	2007	2008	2009	2010	2007	2008	2009	2010
$Constant$	-3.86	-0.78	0.10	0.17	0.18	-0.13	-0.17	-0.09	-3.85	-0.78	0.10	0.17
UR_{t-1}	-0.00	0.00	0.00	0.00	-	-	-	-	-	-	-	-
LE_{t-1}	-	-	-	-	0.00	0.00	0.00	-0.01	-	-	-	-
EM_{t-1}	-	-	-	-	-	-	-	-	-0.00	0.00	0.00	0.00
$LnCommitment_i$	-0.81	-0.07	0.01	-0.00	-0.01	-0.02	0.01	0.00	-0.81	-0.07	-0.01	-0.00
LL_i	-0.83	-0.06	-0.03	-0.05	-0.04	-0.04	0.00	-0.02	-0.83	-0.06	-0.03	-4.81
BT_{it}	-4.42	-0.47	-0.07	0.55	-0.02	-0.23	0.02	0.10	-4.42	-0.46	-0.06	-0.56
AL_{it}	4.67	0.59	0.11	0.54	0.01	0.24	-0.07	-0.14	4.67	0.59	0.11	-0.54
Gar_{it}	-0.01	-0.00	0.00	0.00	0.00	-0.04	0.00	0.00	-0.00	0.00	0.00	0.00
BCC_i	7.93^{**}	10.67^{**}	0.20^{**}	-0.31^{**}	0.02	0.29^{**}	0.00	0.03	7.94^{**}	1.07^{**}	0.20^{**}	-0.30^{**}
$Other\ Lender_i$	7.01	10.47^{**}	0.16^{*}	-0.33^{**}	0.01	0.28	-0.03	0.02	7.02	1.05^{**}	0.16^{*}	-0.33^{**}
$Main\ lender\ Size_i$	0.15	0.02	0.00	0.02^{*}	-0.00	0.00	0.00	0.00	0.14	0.02	0.00	0.02^{*}
$Main\ lender\ Risk_i$	-8.17	0.00	4.13	-0.22^{*}	-0.00	9.14	-2.88	-0.45	-8.16	0.00	4.12	-0.22^{*}
$N°\ Banks_i$	2.74	-0.17	-0.03	-0.20	1.08	-0.10	0.09	-0.00	2.74	-0.17	-3.82	-0.20
$\%\ Main\ Bank\ _i$	0.64^{*}	0.07^{*}	0.01^{*}	0.01^{*}	0.00^{*}	0.02^{*}	0.00^{*}	0.01	0.64^{*}	0.07^{*}	0.00^{*}	0.01^{*}
Obs.	8255	11884	23853	24890	8255	11884	23853	24890	8255	11884	23853	24890
R^2	0.15	0.26	0.07	0.10	0.06	0.07	0.03	0.02	0.15	0.26	0.07	0.10

Source: Bank of Italy's data processed by the authors

Table A.1. The role of multiple exposures in explaining the Exposure at Default – 3 month time horizon

	UR_t				LE_t				EM_t			
	2007	2008	2009	2010	2007	2008	2009	2010	2007	2008	2009	2010
$Constant$	-3.86	-0.78	-0.10	0.17	-3.86	-0.79	-0.10	0.17	-3.86	-0.79	-0.10	0.17
UR_{t-1}	-0.00	0.00	0.00	0.00	-	-	-	-	-	-	-	-
LE_{t-1}	-	-	-	-	-0.00	0.00	0.00	0.00	-	-	-	-
EM_{t-1}	-	-	-	-	-	-	-	-	-0.00	0.00	-0.00	-0.00
$LnCommitment_i$	-0.81	-0.07	-0.01	-0.00	-0.81	-0.07	-0.01	-0.00	-0.81	-0.07	-0.01	-0.17
LL_i	-0.83	-0.06	-0.03	-0.05	-0.83	-0.06	-0.03	-0.05	-0.83	-0.06	-0.03	-0.05
BT_{it}	-4.42	-0.47	-0.06	-0.55	-4.42	-0.47	-0.06	-0.56	-4.43	-0.47	-0.06	-0.55
AL_{it}	4.67	0.59	0.11	0.54	4.67	0.59	0.11	-0.54	-4.67	-0.59	0.11	0.54
Gar_{it}	-0.00	0.00	0.00	-0.00	-0.00	-0.00	0.00	-0.00^{**}	-0.00	-0.00	0.00	-0.00
BCC_i	7.94^{**}	1.07^{**}	0.20^{**}	-0.31^{**}	7.93^{**}	1.07^{**}	0.20^{**}	-0.31^{**}	7.94^{**}	1.07^{**}	0.20^{**}	-0.31^{**}
$Other\ Lender_i$	7.01	1.05^{**}	0.16^{*}	-0.33^{**}	7.01	1.05^{**}	0.16^{*}	-0.33^{*}	7.02	1.05^{**}	0.16^{*}	-0.33^{**}
$Main\ lender\ Size_i$	0.15	0.02	0.00	0.02^{*}	0.15	0.02	0.00	0.02^{*}	0.15	0.02	0.01	-0.02^{*}
$Main\ lender\ Risk_i$	-8.17	0.00	4.12	-0.22^{*}	-8.17	0.00	4.13	-0.22	-8.17	0.00	4.13	-0.22
$N°\ Banks_i$	2.74	-0.17	-0.04	-0.20	2.74	-0.17	-0.04	-0.20	2.74	-0.17	-3.82	-0.20
% $Main\ Bank\ _i$	0.64^{*}	0.07^{*}	0.01^{*}	0.01^{*}	0.64^{*}	0.07^{*}	0.01^{*}	0.01^{*}	0.64^{*}	0.07^{*}	0.01^{*}	0.01^{*}
Obs.	8255	11884	23853	24890	8255	11884	23853	24890	8255	11884	23853	24890
R^2	0.15	0.26	0.07	0.10	0.15	0.26	0.07	0.10	0.15	0.26	0.07	0.10

Source: Bank of Italy's data processed by the authors

Table A.1. The role of multiple exposures in explaining the Exposure at Default – 6 month time horizon

	UR_t				LE_t				EM_t			
	2007	2008	2009	2010	2007	2008	2009	2010	2007	2008	2009	2010
$Constant$	-3.86	-0.79	-0.10	0.17	-3.86	-0.78	-0.10	-0.16	-3.86	-0.78	-0.10	0.17
UR_{t-1}	-0.00	0.00	0.00	0.00	-	-	-	-	-	-	-	-
LE_{t-1}	-	-	-	-	-0.00	0.00	0.00	0.00	-	-	-	-
EM_{t-1}	-	-	-	-	-	-	-	-	-0.00	0.00	-0.00	-0.00
$LnCommitment_i$	-0.81	-0.07	-0.01	-0.00	-0.81	-0.07	-0.01	-0.00	-0.81	-0.07	-0.01	-0.01
LL_i	-0.83	-0.06	-0.02	-0.05	-0.83	-0.06	-0.03	-0.05	-0.83	-0.06	-0.03	-0.05
BT_{it}	-4.42	-0.47	-0.06	-0.55	-4.42	-0.47	-0.06	-0.55	-4.42	-0.46	-0.06	-0.55
AL_{it}	4.67	0.59	0.11	0.54	4.67	-0.59	0.11	-0.54	4.67	-0.59	-0.11	0.54
Gar_{it}	-0.00	-0.00	0.00	0.00	-0.00	0.00	0.00	-0.00	-0.00	-0.00	0.00	0.00
BCC_i	7.94**	1.06**	0.20**	-0.30**	7.94**	1.07**	0.20**	0.31**	7.94**	1.06**	0.20**	-0.31**
$Other\ Lender_i$	7.02	1.05**	0.16*	-0.33**	7.01	1.05**	0.16*	0.33**	7.01	1.05**	0.17*	-0.33**
$Main\ lender\ Size_i$	0.15	0.02	0.01	0.02*	0.15	0.02	0.00	0.02*	0.15	0.02	0.00	0.02*
$Main\ lender\ Risk_i$	-8.17	0.00	4.13	-0.22	-8.17	0.00	4.13	-0.22*	-8.16	0.00	4.13	-0.22
$N°\ Banks_i$	2.74	-0.17	-0.03	-0.20	2.74	-0.17	-0.04	-0.20	2.74	-0.17	-0.04	-0.20
$\%\ Main\ Bank\ _i$	0.64*	0.07*	0.01*	0.01*	0.64*	0.06*	0.01*	0.01*	0.64*	0.07*	0.01*	0.01*
Obs.	8255	11884	23853	24890	8255	11884	23853	24890	8255	11884	23853	24890
R^2	0.15	0.26	0.07	0.10	0.15	0.26	0.07	0.10	0.15	0.26	0.07	0.10

Source: Bank of Italy's data processed by the authors

Table A.1. The role of multiple exposures in explaining the Exposure at Default – 9 month time horizon

	UR_t				LE_t				EM_t			
	2007	2008	2009	2010	2007	2008	2009	2010	2007	2008	2009	2010
$Constant$	-3.86	-0.78	-0.10	0.17	-3.85	0.79	-0.10	0.17	-3.86	-0.79	-0.10	0.17
UR_{t-1}	-0.00	0.00	0.00	0.00	-	-	-	-	-	-	-	-
LE_{t-1}	-	-	-	-	-0.00	0.00	0.00	0.00	-	-	-	-
EM_{t-1}	-	-	-	-	-	-	-	-	-0.00	0.00	0.00	0.00
$LnCommitment_i$	-0.81^{**}	-0.07	-0.01	-0.00	-0.81	-0.07	-0.01	-0.00	-0.81	-0.07	-0.01	-0.00
LL_i	-0.83	-0.06	-0.03	-0.05	-0.83	-0.06	-0.03	-0.05	-0.83	-0.06	-0.03	-0.05
BT_{it}	-4.42	-0.46	-0.06	-0.55	-4.43	-0.47	-0.06	-0.55	-4.42	-0.46	-0.06	-0.56
AL_{it}	4.67	0.59	0.11	0.54	4.67	0.59	0.11	0.54	4.67	0.59	0.11	0.54
Gar_{it}	-0.00	-0.00	0.00	-0.00	-0.00	-0.00	0.00	-0.00	-0.00	0.00	0.00	0.00
BCC_i	7.94^{**}	1.07^{**}	0.20^{**}	-0.30^{**}	7.93^{**}	1.06^{**}	0.20^{**}	-0.31^{**}	7.93^{**}	1.07^{**}	0.20^{**}	-0.30
$Other\ Lender_i$	7.02	1.05^{**}	0.16^{*}	-0.33^{**}	7.01	1.04^{*}	0.16^{*}	-0.33^{**}	7.01	1.05^{**}	0.16^{*}	-0.33
$Main\ lender\ Size_i$	0.15	0.02	0.00	0.02^{*}	0.14	0.02	0.00	0.02^{*}	0.15	0.02	0.00	0.02
$Main\ lender\ Risk_i$	-8.17	0.00	4.13	-0.22	-8.16	0.00	4.12	-0.22^{*}	-8.16	0.00	4.13	-0.22
$N°\ Banks_i$	2.74	-0.17	-0.04	-0.20	2.74	-0.17	-0.04	-0.20	2.74	-0.17	-0.04	-0.20
$\%\ Main\ Bank\ _i$	0.64^{*}	0.07^{**}	0.01^{*}	0.00^{*}	0.64^{*}	0.07^{*}	0.00^{*}	0.01^{*}	0.64^{*}	0.07^{*}	0.01^{*}	0.01^{*}
Obs.	8255	11884	23853	24890	8255	11884	23853	24890	8255	11884	23853	24890
R^2	0.15	0.26	0.07	0.10	0.15	0.26	0.07	0.10	0.15	0.26	0.07	0.10

Source: Bank of Italy's data processed by the authors