Bank organization and credit supply at difficult times: Evidence from the Lehman Crisis*

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Abstract

Do banks with different internal organizations react differently to exogenous shocks? Are some organizational structures better at helping 'good' firms facing temporary difficulties, but with high total factor productivity and better economic fundamentals and prospects? We answer this question by analyzing lending relationships of a representative sample of Italian non-financial firms in the 6-month period after Lehman's failure. Controlling for credit demand with firm's fixed effects, we find that banks with internal organization that allow for a better use of soft information – because they have a smaller number of hierarchical levels and are specialized in lending to smaller, and typically more opaque firms – granted relatively more credit than other banks. Smaller firms also experienced a stronger reduction in credit supply from those same banks that have an internal organization that is less suitable to the transfer of soft information. Finally, banks specialized in dealing with SME lending show a better ability to help firms with higher productivity but under temporary financial distress (i.e., higher short-term risk).

Keywords: credit crunch; lending strategies; bank organization.

JEL codes: E44, E51, G21.

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1. Introduction

Banks have very different organizational structures and lending technologies, ranging from the "relationship-based" model of small banks with limited hierarchical structure (e.g., soft-information based lending to SMEs), to "transactions-based" models pursued by larger financial intermediaries (e.g., financial statement lending and credit scoring; Berger and Udell, 2006; Udell, 2009 and 2015).

Do banks with different lending strategies react differently at times of crisis? Are some organizational structures better at helping 'good' firms, with higher total factor productivity better economic fundamentals and prospects? We try to answer this question by analyzing lending relationships for a representative sample of Italian non-financial firms in the 6-month period after Lehman's failure.

There are several reasons why bank organizational structure might affect banks' ability to identify and financially support the best firms. For example, the higher dependence of large banking groups on transaction-based lending might imply a lower ability to recognize borrower's quality, in terms of economic fundamentals and prospects, compared to banks which have accumulated soft information through credit relationships. But other factors might work in the opposite direction. Assessing highly innovative projects in a given sector can be easier for large banking groups, that may have broader sector expertise or even dedicated business units that are specialized in funding innovation. Also, to the extent that the most productive projects (i.e., those with the highest net present value) are on average riskier, large banking groups, which have a larger loan portfolio and therefore better diversification opportunities, might be more willing to fund them. Furthermore, small local banks focused on credit relationships might find themselves 'trapped' in those relationships, for example because of long-standing personal relationships between the local loan officer and the entrepreneur, and might find more difficult to reallocate resources in favour of the most promising customers.

For all these reasons, measuring the link between bank organization and borrower's quality is essentially an empirical question. In this paper, we address this question by analyzing bank-firm level data on the lines of credit of a representative sample of roughly 3,300 Italian non-financial firms in manufacturing and services; such firms borrow from a set of about 500 banks, spanning a total of almost 24,000 bank-firm observations (each firm, therefore, borrows from more than 5 banks, on average). We focus on the 6-month period after Lehman's failure, when credit collapsed world-wide and, according to the evidence available, constraints to credit supply, related to bank capitalization and liquidity, were more binding (e.g. Albertazzi and Marchetti, 2010; Gambacorta and Mistrulli, 2014; Cingano et al. 2016; Bonaccorsi di Patti and Sette, 2016). We choose to focus on lines of credit since they are arguably more variable and more supply-driven than other types of loans.

Our analysis has two distinctive and innovative features. First, we distinguish banks' organizational structures and lending strategies based on the results of a survey conducted by the Bank of Italy just before the financial crisis across all Italian banks. Using these information, we can categorize banks according to characteristics of their internal organization and lending technology. For example, we have information on whether the bank is organized in divisions, how many hierarchical layers it has, whether it is an entity specialized in small business lending within a larger banking group, whether it uses credit scoring techniques. As forcefully argued by Stein (2002), Berger et al. (2005), and Alessandrini et al. (2009 and 2010), banks with different organizations have a different ability to process information and for this reason adopt different lending technologies.

Second, we measure borrower's quality not only using financial indicators, but also using a more forward-looking TFP-based measures of economic fundamentals. This can indeed be crucial, since balance sheet measures may be poorly correlated with economic fundamentals, especially during a deep recession or a financial crisis, when firms' balance sheets may significantly deteriorate, regardless of the underlying fundamentals. For example, a firm which has regained its competitiveness through debt-funded restructuring may be financially weak while enjoying good economic fundamentals and growth prospects.

Since our sample include a large number of firms with multiple lending relationships, as it is typical of the Italian banking market (Detragiache et al., 2000), we can adopt an identification strategy that allows to control for firm's credit demand (and any other firm characteristic, including credit risk) through firm-specific fixed effects, as in Khwaja and Mian (2009). Our results are therefore robust to a number of criticisms that may emerge from the potential endogeneity of lending relationships.

The main results of our analysis is that banks with internal organization that allow for a better use of soft information – because they have a smaller number of hierarchical levels and are specialized in lending to smaller, and typically more opaque firms – granted relatively more credit than other banks in the aftermath of Lehman's crisis. More importantly, larger and more complex banks reduced credit supply relatively more to smaller firms than to larger borrowers, confirming the anecdotal evidence that the impact of the 2007-2008 financial crisis on bank credit supply was not homogeneous across lender and borrower types. Finally, banks with specific organizations devoted to SME lending granted relatively more credit than other banks to firms that were likely to be facing temporary problems, because even if they were classified as risky, had at the same time high productivity.

The rest of the paper is organized as follows. The next section reviews the most relevant literature related to our research. Section 3 describes the data used in the empirical analysis and presents some descriptive statistics on the lending patterns of banks with different organization structures during the crisis. Section 4 describes the identification strategy of our empirical models and presents the results of the econometric analysis. Section 5 concludes.

2. Related literature

This paper contributes to the empirical literature studying the impact of different bank organizational structures and lending strategies on credit supply, with a particular focus on the reaction during market turmoil.

It is well-known that larger banks are likely to have greater difficulties in producing and processing soft information, and thus may have a comparative advantage in transaction-based lending (based on financial statements and credit scoring) rather than relationship-based lending (e.g. Berger and Udell, 2006; Berger et al., 2005; Liberti and Mian, 2009). This can be seen in terms of the primary source of information on which different lending strategies are based, i.e., “soft” information vs. “hard” information. Unlike “hard” information, “soft” information is not easily quantified and transmitted within the hierarchy of a financial institution (Stein 2002; Berger et al. 2005). The flip side of the coin is that smaller banks are unlikely to be able to reap the full benefits of using standardized technologies such as those used in transaction based lending, that is based on “hard” information.

These technological constraints have a number of well-known consequences on firms’ credit availability. For example, larger banks tend to lend less to smaller and more opaque firms. But this does not necessarily mean that large banks do not lend to SMEs, but rather that they focus on the most transparent and leave smaller banks to use relationship lending with more opaque SMEs. Nonetheless, in some market segments it is widely recognized that credit scoring can add significant value to the lending business, and indeed many small banks use nowadays credit scores to complement their traditional information collection.

Of course, different organizational structures can entail a very different impact on bank credit supply in normal times and during times of crisis. In fact, the widespread credit-crunch caused by the 2007-2008 financial crisis was anything but uniform across banks. DeYoung et al. (2015), for example, show that during the crisis some small business lenders in US did not cut but actually increased their credit supply to small businesses, leveraging on their ability in using the information produced by relationship lending to increase their market shares (see also DeYoung, 2015). Indeed, the risk adjusted returns from transaction based lending can be very different in normal times, when the average behavior of the borrower can be taken as a reliable reference point, and during a crisis, when instead accounting for tail risk is much more important. Del Prete et al. (2017) present additional evidence on the role of bank organizational structure is provided in a recent paper on the impact of the 2007-2008 financial crisis in Italy. Using data at the bank level, they show that financial intermediaries more prone to use credit scoring techniques reduced their lending relatively more than others, while those that delegated more power to their branch managers had more lenient lending policies. However, since their analysis is based on bank level data, it cannot adopt an identification strategy that allows to adequately control for firm’s credit demand.

Our paper contributes to this debate by showing that, during the 2007-2008 financial crisis, banks with an organizational structure more oriented towards transaction lending technologies cut credit more than banks more specialized in the use of information obtained from relationship lending, and made somehow better use of information coming from measures of longer run prospects, such as the level of total factor productivity, even in the case of firms showing higher levels of short-term risk.

3. Data and descriptive statistics

Our analysis is based on information on bilateral bank-firm relationships, complemented with data on bank specific and firm specific characteristics, that cover a representative sample of Italian banks and firms around the time of the Lehman crisis, i.e. September 2008 to March 2009. We use five very high quality data sources. Information on the value of the lines of credit to each firm in our sample, and the interest charged on them, comes from the Italian Credit Register, a special unit of the Bank of Italy (Centrale dei Rischi) that collects detailed information on all individual lines of credit extended in Italy above the value of euro 30,000. Data on firm characteristics come from two different sources: the Company Accounts Data Service (CADS - Centrale dei Bilanci), that is managed by a consortium that includes the Bank of Italy and all the major Italian commercial banks and collects high quality balance sheet data for a large number of Italian firms; and the Survey of Industrial and Service Firms (SISF), carried out annually by the Bank of Italy, that includes a large set of quantitative and qualitative information on a stratified sample of firms, representative of the entire Italian manufacturing sector. Data on bank characteristics also come from two different sources: bank balance sheet data are drawn from the Banking Supervision Register at the Bank of Italy; data on bank organization are from a Survey conducted by the Bank of Italy on a large sample of Italian banks, and refer to the end of 2006.

Overall, the dataset includes about 24,000 observations on bank-firm lines of credit, and about 14,000 on the interest rates charged. They refer to 521 banks lending to more than 3,000 firms. On average, firms in our sample borrow from more than 5 different banks.

Our main dependent variable is the change in outstanding lines of credit extended by bank *b* to firm *f*, divided by the firm's total assets at the beginning of the period. We preferred to use this variable rather than the rate of growth of lines of credit, because in some cases the amount of credit at bank-firm level at the beginning of the period (September 2008) or at the end (March 2009) was negligible, resulting in a disproportionate number of observations with, respectively, a huge positive rate of growth or a rate of growth equal to -100%. We also have information on the change in lines of credit actually used by the firms, that is typically a share of the total value of the lines of credit extended by the bank. Rather than dropping large tails of the distribution of the dependent variable in question, which in all likelihood would have resulted in the elimination of observations with the most interesting information content for our purposes, we chose to normalize the change in credit by firm's total assets.

Table 1 - Main terms of lending between 2008q3 and 2009q1, by firm size

			By firm size							
	Total		1° quartile		2° quartile		3° quartile		4° quartile	
	Mean	Coef. Var.	Mean	Coef. Var.	Mean	Coef. Var.	Mean	Coef. Var.	Mean	Coef. Var.
Change in:										
extended credit lines	-0.13	-16.77	-0.10	-23.20	-0.18	-12.50	-0.10	-19.23	-0.06	-23.46
used credit lines	-0.09	-24.83	-0.16	-16.57	-0.09	-24.79	-0.03	-62.02	-0.01	-180.78
interest rates	-0.42	-6.04	-0.35	-7.00	-0.38	-6.92	-0.52	-4.70	-0.60	-4.63
No. of lending relationships	10.75	0.61	8.02	0.59	10.12	0.49	12.83	0.52	17,00	0.66

Table 1 and Figure 1 report the average changes in the value of outstanding lines of credit extended by banks and used by borrowers, distinguishing by firm size. Interestingly, although the value of extended and used lines of credit drops for all firms, the contraction is stronger in the case of smaller firms. Similar, larger firms were granted a higher drop in interest rates. Finally, he number of lending relationships ranges from 8 for small firms to 20 for large firms. In average they are a bit less than 11.

Figure 1 - Change in extended and used lines of credit between 2008q3 and 2009q1, by firm size

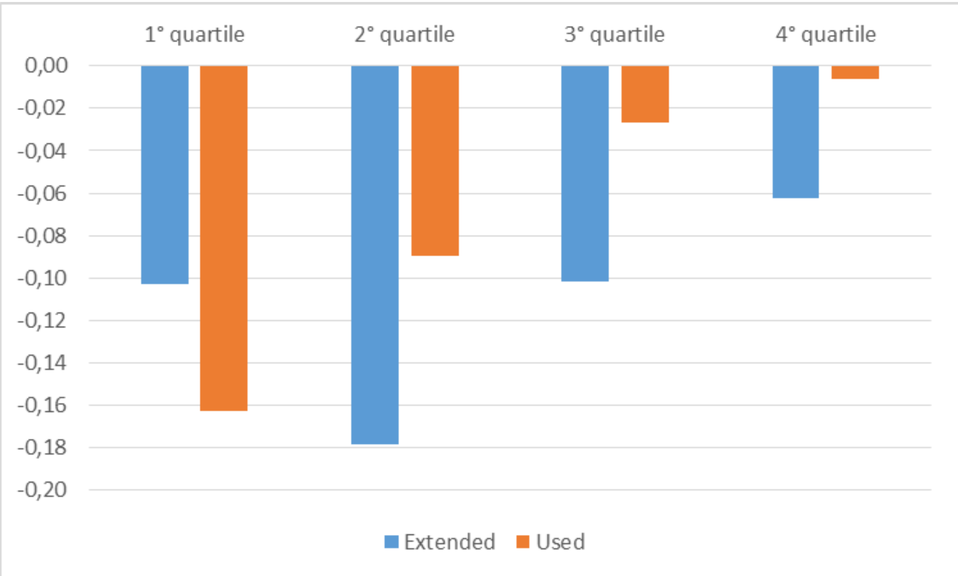

Table 2 and Figure 2 report the same average changes in the value of outstanding lines of credit extended by banks and used by borrowers, but distinguishing by bank size.

Table 2 - Change in main terms of lending between 2008q3 and 2009q1, by bank size

			By firm size							
	Total		1° quartile		2° quartile		3° quartile		4° quartile	
	Mean	Coef. Var.	Mean	Coef. Var.	Mean	Coef. Var.	Mean	Coef. Var.	Mean	Coef. Var.
Change in:										
extended credit lines	-0,13	-16,67	0,33	4,69	0,17	8,34	0,16	11,16	-0,17	-13,06
used credit lines	-0,09	-24,71	0,26	5,92	0,07	26,08	0,06	35,91	-0,11	-20,08

In this case, smaller banks actually increased the value of extended and used lines of credit over firm's total assets, while only banks in the largest quartile of the distribution by total assets reduced lending. This is fully consistent with the ample available evidence that the crisis triggered by Lehman's default hit mainly the largest banks, leaving to smaller intermediaries the possibility to increase their market shares.

Figure 2 - Change in extended and used lines of credit between 2008q3 and 2009q1, by bank size

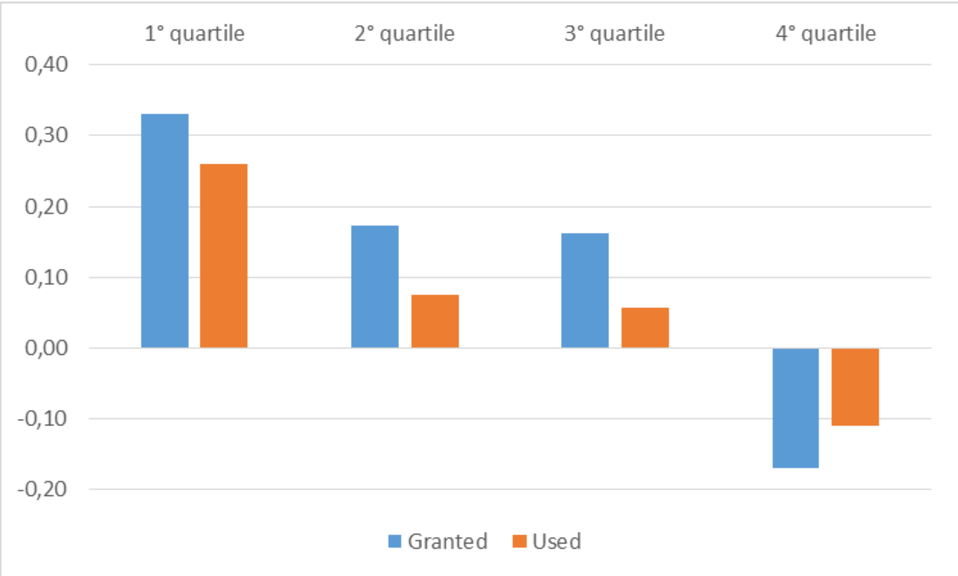

Table 3 presents some descriptive statistics on the characteristics of the banks in our sample, focusing in particular on those describing their organizational structures, that are the focus of our paper. The average size of banks in our sample is rather small, since we include a large number of credit cooperative institutions, that typically operate in small areas, with only a few branches. However, as it is customary in any analysis at the bank level, the variation is very high, due to the presence of some very large banks. Leverage is relatively low, as it is shown by the high value of the ratio of capital to total assets, while the share of liquid assets is not very high, just below 13 per cent.

The following set of variables in Table 3 are our proxies for the organizational structure adopted by the bank. Just below 10 per cent of the financial intermediaries in our sample are units specialized in SME lending within a larger banking group. Interestingly, 27 per cent of the banks in our sample have an internal organization in divisions, distinguishing clients between retail and corporate. The vast majority of banks in our sample operate at the level of the province, that is at the level of one of the about 100 administrative units in which the Italian territory is roughly evenly divided. This is confirmed by values around 2 of the measures of geographical coverage, that is the number of provinces where the bank operates a branch. Clearly, while this is due to the presence of a large number of small banks, our sample also includes all the large Italian banks operating all over the country. The number hierarchical levels in which the banks in our sample are organized ranges from 1 to 18, a rather large number. Considering the large number of small bank in our sample, the average value between 5 and 6 suggests that Italian banks adopt a rather vertical organizational structure. Finally, 56 per cent of the banks in our sample use credit scoring techniques, suggesting that these tools are widely adopted, most likely also by smaller financial intermediaries.

Table 3 - Bank characteristics

	Mean	Coeff. of var.
Total assets (billions of euros)	0.57	4.63
Capital to total assets (percentage)	15.66	0.60
Liquid assets to total assets	12.94	0.68
Specialized SMEs	0.09	3.25
Divisions	0.27	1.63
Geographical coverage SMEs	1.86	1.13
Geographical coverage large firms	2.24	0.91
Hierarchical levels SMEs	5.52	0.33
Hiearchical levels large firms	5.55	0.43
Scoring	0.59	0.83

Table 4 presents the three most important characteristics of the firms in our sample: productivity, profitability, and riskiness. Productivity is computed for each firm as the log-level of the Solow residual calculated on gross output. Since the level of productivity may vary widely across sectors, for each firm we computed the difference relative to the sector median, to allow for comparison across sectors. Robustness analysis has been conducted by using alternative measures of TFP, such as that proposed by Olly and Pakes (1996), with and without the adjustments suggested by, respectively, Klette and Griliches (1996), Levinsohn and Petrin

(2003) and Melitz (2000). The coefficient of variation shows that there are large differences in productivity across firms. Profitability is measured as the ratio of total returns to total assets, a rather more reliable measure than return on equity in the case of small firms. On average, the firms in our sample have a rather low profitability, but Also in this case the coefficient of variation is extremely large, suggesting the presence of significant heterogeneity across firms.

Table 4 – Firm characteristics

	Mean	Coefficient of variation
Total factor productivity	-0,01	-116,09
Returns on assets	0,01	5,34
Riskiness	4,47	0,40

Finally, firm riskiness is measured by the Z-score, an indicator of the probability of default of a given firm computed annually by the Company Accounts Data Service (CADS) on balance sheet variables according to the methodology suggested by Altman (1968) and Altman et al. (1994), and taking values from 1 for the less risky firms to 9 for the riskiest firms. In the econometric analysis we follow the classification suggested by CADS and define as low-risk firms those with a Z-score between 1 and 3, as 'medium risk' firms those in the 4-6 range, and as 'high risk' those with a Z-score in the 6-9 range.

Table 5 presents the bilateral correlations among the main variables used in the empirical analysis, calculated on the whole regression sample of between 14,000 and 24,000 observations, depending on the set of variables considered. The change in the ratio of extended and used lines of credit to total firm assets have a strong positive correlation, as expected. Interestingly, there is no significant correlation between the change in lines of credit extended and the size of the bank granting them, while there is evidence of a positive correlation with the amount of bank capital. Coming to the characteristics of the bank's organizational structure, we find that several of them are significantly correlated with the changes in the value of extended and used lines of credit across the financial crisis. In particular, we find a positive correlation with being a unit specialized in SME lending within a larger banking group and, while we find a negative correlation with being a bank that is organized with a larger number of hierarchical levels. Quite surprisingly, we do not find any statistically significant correlation with the use scoring techniques, and with the organization in divisions. Finally, Table 5 shows that the changes in lines of credit are positively correlated with firms' profitability and negatively correlated with their riskiness, while there is no statistically significant bilateral relationship with productivity, size and the number of lending relationships.

Descriptive statistics and bilateral correlations can only provide some preliminary evidence consistent with the hypothesis that bank organizational structures affect credit supply during a crisis. Indeed, they do not allow to disentangle the effect of changes on credit supply, the focus of our analysis, from those on credit demand. For these reasons, we now move to a more rigorous econometric analysis.

Table 5 – Bilateral correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. Change in ext. credit lines																		
2. Change in used credit lines	0,7414*																	
3. Credit line interest rate	0,0251*	0,0408*																
4. Sh. of bank lines of credit	-0,1527*	-0,1268*	0,0131															
5. Bank total assets (log)	-0,0075	-0,0103	0,0779*	0,0704*														
6. Bank Capital to asset ratio	0,0950*	0,0714*	0,0126	0,0465*	0,2007*													
7. Bank liquid to total assets	-0,0065	0,0010	-0,0018	0,0101	-0,5673*	0,0431*												
8. Bank specialized SMEs	0,1138*	0,0760*	0,1074*	0,0077	0,2186*	-0,2431*	-0,1419*											
9. Bank with divisions	-0,0068	-0,0062	0,0328*	0,0480*	0,3988*	0,1622*	-0,3898*	0,1343*										
10. Bank geo. coverage SMEs	-0,0648*	-0,0539*	-0,0152	0,0709*	0,4998*	0,5068*	-0,1133*	-0,0264*	0,2269*									
11. Bank geo. cov. large firms	0,0822*	0,0570*	-0,0085	-0,0099	0,2642*	0,4495*	-0,1876*	0,0227*	0,3182*	0,4433*								
12. Bank hierarchy lev. SMEs	-0,1056*	-0,0810*	0,0085	0,0419*	0,2600*	-0,0442*	-0,1644*	0,0596*	0,3255*	0,2792*	-0,0136							
13. Bank hierarchy lev. large fir.	-0,0914*	-0,0704*	-0,0020	0,0581*	0,3127*	0,0959*	-0,1693*	0,0326*	0,2782*	0,4389*	-0,1205*	0,9083*						
14. Bank using scoring tech.	-0,0068	-0,0050	0,0436*	0,0135	0,3933*	-0,0077	-0,2964*	0,0889*	0,3915*	0,0588*	0,1094*	0,1474*	0,0961*					
15. Firm ROA	0,0323*	0,0323*	-0,0446*	-0,0021	0,0133*	0,0032	-0,0135*	0,0020	-0,0014	0,0120	0,0034	0,0149*	0,0139	-0,0003				
16. Firm TFP	0,0098	0,0091	-0,1369*	-0,1442*	0,0166*	-0,0133*	-0,0445*	-0,0158*	-0,0252*	0,0192*	0,0032	0,0154*	0,0232*	-0,0193*	0,3909*			
17. Firm no. lending rel.	-0,0030	0,0021	-0,1702*	-0,4476*	-0,0806*	-0,0379*	0,0073	-0,0498*	-0,0637*	-0,0462*	-0,0093	-0,0260*	-0,0267*	-0,0425*	0,0211*	0,3212*		
18. Firm size	0,0047	0,0122	-0,1466*	-0,2092*	0,0386*	-0,0142*	-0,0517*	-0,0063	-0,0352*	0,0234*	0,0063	0,0233*	0,0305*	-0,0173*	0,0978*	0,3365*	0,3842*	
19. Firm Z-score	-0,0358*	-0,0273*	0,0258*	-0,1551*	-0,0386*	-0,0247*	0,0275*	0,0034	-0,0217*	-0,0259*	-0,0085	-0,0246*	-0,0199*	-0,0015	-0,5567*	-0,3148*	0,1908*	-0,0829*

4. Econometric analysis

4.1 The baseline empirical models

The aim of our empirical analysis is to establish whether banks with different organization structures react differently to external shocks. To this purpose, the collapse of Lehman Brothers is a natural experiment for investigating the role of bank organization on credit supply. This is even more the case when focusing on the Italian banking sector, that was indeed hit by the crisis, but whose banks were not directly exposed to the sectors where the crisis first erupted. For this reason, our empirical model focuses on the two quarters following Lehman's default.

Our first specification aims at verifying if firm characteristics explain in part the change in the value of the bank lines of credit extended to them, while controlling for any reason that might have caused a differential effect in bank credit supply by including bank dummies. In practice, our analysis begins by estimating the following equation:

$$\Delta\left(\frac{loans_{bf}}{total\ assets_{f}}\right)_{2009q1-2008q3} = \alpha + \beta\ x_{bf} + \gamma\ ydummy_{b} + \delta\ z_{f} + \varepsilon_{bf} \qquad (1)$$

where: $\Delta\left(\frac{loans_{bf}}{total\ assets_{f}}\right)_{2009q1-2008q3}$ is the change in the ratio of lines of credit extended by bank *b* to firm *f* between the first quarter of 2009 and the third quarter of 2008; x_{bf} are characteristics of the lending relationship between bank *b* and firm *f*; $dummy_b$ are bank level dummies; z_f are firm characteristics; and ε_{bf} is a standard error term.

Next, we move to the estimation of the impact of bank characteristics on credit supply. Since we are interested in identifying if and to what extent banks' organization has impacted on credit supply at the time of the shock, it is of foremost importance that we control for credit demand. Indeed, if we failed to do so we would attribute any change in a firm's loan demand to the banks' decisions. But, to the extent that the financial crisis started having substantial effects on the real economy in the course of 2008, it is not possible to exclude that firms cut their credit demand between 2008q3 and 2009q1. Therefore, there is a high risk that, not controlling for credit demand, we would not obtain reliable estimates of credit supply effects.

We control for credit demand using a robust approach that exploits the large diffusion of multiple banking relationships in Italy (and in our sample). Similar to Khwaja and Mian (2008), we include in our specification a dummy variable for each firm. In practice, our framework allows to answer the following question: in the Aftermath of Lehman's default, did banks with a given organization structure (for example a large number of internal hierarchical layers) change their credit supply to the same firm differently from banks with a different organization structure (for example a flatter hierarchy)?

Clearly, by introducing firm dummies, we can no more estimate the impact of firm characteristics on the change in bank credit that is extended to each firm. However, we can still investigate whether banks with a given organization changed their credit supply differently. In practice, we can estimate the following specification:

$$\Delta\left(\frac{loans_{bf}}{total\ assets_{f}}\right)_{2008q3-2009q1} = \alpha + \beta\, x_{bf} + \gamma\, y_{b} + \delta\, dummy_{f} + \varepsilon_{bf} \qquad (2)$$

where the coefficient γ measures the average impact of bank characteristics on the change in credit supply by bank *b*.

4.2 Results of the baseline models

Table 6 presents the results of the estimation of equation (1), that includes firm characteristics and bank dummies. While this specification does not allow to answer the key research question of our paper, that is the whether bank organization impacted on credit supply after the Lehman crisis, it provides some interesting information.

Table 6 – Change in credit supply and firm level characteristics

	(1)	(2)	(3)	(4)	(5)
Small firms (1° quartile dummy)	-0.528*** (0.150)	-0.484*** (0.145)	-0.391*** (0.142)	-0.318** (0.146)	-0.726*** (0.158)
Small to medium firms (2° quartile dummy)	-0.325** (0.135)	-0.304** (0.130)	-0.217* (0.127)	-0.165 (0.134)	-0.499*** (0.139)
Medium firms (3° quartile dummy)	-0.131 (0.126)	-0.112 (0.128)	-0.0547 (0.126)	-0.0321 (0.128)	-0.233* (0.130)
Firm returns on assets	5.318*** (2.060)		7.018*** (1.905)		
Firm total factor productivity	0.338*** (0.104)			0.314*** (0.0916)	
Firm number of lending relationships	-0.502*** (0.116)				-0.413*** (0.110)
Share of total bank lines of credit of the firm	-6.880*** (0.689)	-5.973*** (0.559)	-5.927*** (0.558)	-5.850*** (0.556)	-6.857*** (0.689)
Interest rate on bank credit line	-0.00972 (0.0154)	-0.00172 (0.0145)	-0.00174 (0.0145)	0.00239 (0.0148)	-0.0119 (0.0152)
Firm riskiness	0.00994 (0.0321)	-0.0826*** (0.0272)	-0.0240 (0.0312)	-0.0691** (0.0273)	-0.0549* (0.0282)
Number of observations	10,064	10,064	10,064	10,064	10,064
adj. R-sq	0.298	0.296	0.296	0.296	0.297

Indeed, the negative and statistically significant coefficients of the dummies for firms in the first and second quartile of the distribution by size show that credit dropped significantly more for smaller firms. Lines of credit extended by banks with a larger share of total bank credit to the firm also dropped more, but this is clearly due to the fact that we measure changes in absolute terms, and larger lines of credit certainly had more room to drop by larger amounts. Reassuringly, lending dropped less for firms with higher profitability, measured by their returns on assets, and productivity, measured by the level of the total factor productivity. Interestingly, the coefficient of riskiness, measured by the Z-score, is negative, but it is not always statistically significant. Finally, there is no evidence of an effect of the cost of credit on the change in bank lines of credit.

Clearly, this results do not allow to disentangle demand effects from supply effects: a relatively smaller drop in credit to more profitable firms may be due to the fact that these firms cut credit demand relatively less, for example because they operated in sectors that maintained significant profit opportunities, or that banks were more willing to lend to them, because they foresee a higher probability that the loan would be repaid. However, this specification allows to control for the aggregate change in credit supply by each bank, through the inclusion of bank fixed effects, and gives us an interesting benchmark for comparison with the results of the following specifications.

Next, we move to the key issue of our paper. Table 7 presents the results of the estimation of equation (2), that includes bank characteristics and controls for credit demand through firm level dummies. Panel (1) shows that both banks that are part of large banking groups (i.e., the five largest banking groups in Italy) and small credit cooperative banks reduced their credit supply during the sample period more than middle size banks (the control group). Not surprisingly, banks with a lower level of capital reduced credit supply more than other banks; on the contrary, bank's liquidity does not have a statistically significant effect. Interestingly, we find that the organization structure has a significant impact on how banks reacted to the crisis. Controlling for other characteristics, banks that within a larger banking group are specialized in SME lending actually increased their credit supply. On the contrary, banks that were organized with a higher number of internal hierarchical layers reduced their credit supply relatively more. Quite surprisingly, the use of credit scoring techniques, a technology suggesting the adoption of arm's length lending strategies, does not have a significant impact on the change in credit supply.

The results reported in Panels (2)-(6) confirm the robustness of the finding that banks with less capital and those organized with a larger number of hierarchical levels cut credit relatively more than other financial intermediaries. On the contrary, in these specifications the positive coefficients of the dummy for banks that within a larger banking group are specialized in SME lending are statistically insignificant. Interestingly, it turns out that not controlling for bank organization, the effect of being part of a very large banking group and of being a credit cooperative become statistically insignificant. This evidence of an omitted variable bias, and the sign of such a bias, suggests that it is not only size that matters in credit supply, but rather what size implies for bank organization. For example, the evidence in Panels (2)-(6) shows that on average banks that are part of one of the five largest Italian banking groups did cut credit relatively more than other banks, if one controls for the positive effect of being a financial intermediary within such a group that is specialized in SME lending. In fact, controlling for such positive effect, it turns out that banks that are part of a very large group cut credit relatively more than others.

Table 7 - Change in credit supply, bank characteristics and firm dummies

	(1)	(2)	(3)	(4)	(5)	(6)
Bank total assets (log)	-0.0202	0.0448	-0.06	0.0537	0.00572	0.0486
	-0.0991	-0.123	-0.147	-0.139	-0.117	-0.146
Five largest banking groups (dummy)	-0.322*	-0.383*	-0.202	-0.212	-0.161	-0.24
	-0.172	-0.201	-0.21	-0.177	-0.204	-0.206
Credit cooperative banks (dummy)	-0.831*	-0.29	-0.288	-0.3	-0.774	-0.28
	-0.476	-0.36	-0.361	-0.415	-0.579	-0.378
Low capital (dummy)	-0.702**	-0.604*	-0.605*	-0.676*	-0.754**	-0.665*
	-0.343	-0.332	-0.31	-0.359	-0.353	-0.35
High liquidity (dummy)	0.313	0.333	0.322	0.324	0.313	0.333
	-0.327	-0.286	-0.336	-0.284	-0.335	-0.291
Bank specialized SMEs (dummy)	0.801*	0.687				
	-0.429	-0.43				
Bank geo. coverage (dummy)	0.0435		0.536*			
	-0.209		-0.295			
Bank organized with divisions (dummy)	-0.00559			-0.0908		
	-0.211			-0.21		
Bank hierarchical levels	-0.850**				-0.74*	
	-0.408				-0.397	
Bank using scoring techniques (dummy)	0.179					-0.024
	-0.253					-0.234
Share of total bank lines of credit of the firm	-0.37	-0.559	-0.43	-0.444	-0.262	-0.442
	-0.519	-0.568	-0.522	-0.534	-0.47	-0.538
Interest rate on bank loan	0.0171*	0.0206*	0.0302***	0.0325**	0.0310**	0.0323**
	-0.00929	-0.00945	-0.011	-0.0126	-0.0142	-0.0126
Number of observations	12,102	12,102	12,102	12,102	12,102	12,102
adj. R-sq	0.102	0.076	0.071	0.062	0.081	0.061

Overall, the results presented in Table 7 provide some support to the view that, during the crisis caused by Lehman’s default, banks with internal organization that allow a better use of soft information – because they have a smaller number of hierarchical levels and are specialized in lending to smaller, and typically more opaque firms – granted relatively more lines of credit than other banks. However, soft information has not the same value for all types of borrowers. Indeed, it is very likely that it is much more relevant in the case of smaller, less productive, riskier, and less profitable firms. For this reason, we then turn to address the issue of the different impact of bank characteristics on different borrower types.

4.3 Firm characteristics and bank organization structures

Our data allow to go move one step forward in our analysis of the impact of bank characteristics lending. Since our sample includes many different banks, we can investigate whether banks with different organizations had a different credit supply policy depending on borrowers' characteristics, while allowing bank fixed effects to control for the average effect of all bank characteristics. This allows to answer the following question: in the Aftermath of Lehman's default, did banks with different characteristics change their credit supply differently depending on firm characteristics? To this aim, we estimate the following specification:

$$\left(\frac{loans_{bf}}{total\ assets_f}\right)_{2008q3-2009q1} =$$

$$= \alpha + \beta\, x_{bf} + \gamma\, dummy_b + \delta\, dummy_f + \vartheta\, y_b * z_f + \varepsilon_{bf} \qquad (3)$$

where the coefficient ϑ captures the differential effect of bank characteristics depending on the features of the firms. In other words, while each bank's average change in credit supply due to its intrinsic characteristics is captured by the coefficient γ associated with the fixed effect, ϑ measures if there is any common pattern across banks with a given characteristic y_b in changing credit supply to firms with a given characteristics z_f. For example, ϑ measures if larger banks cut credit to smaller firms relatively more than smaller banks, controlling for all factors affecting average credit supply by each bank and credit demand by each firm.

4.4 Firm characteristics and bank organization structures

Tables 8-10 present the results of the estimation of equation (3). Each table presents the results of specifications in which bank characteristics are interacted with firm characteristics capturing their size, riskiness and profitability.

Table 8 presents the first set of results, testing whether banks with different characteristics had a different lending policy depending on the size of the borrowers. The results show that this is indeed the case. The negative and statistically significant coefficients for the interaction of the dummy variables for firms belonging to the first and second quartile of the distribution by size confirm that banks are relatively more likely to cut credit to smaller firms if they: a) belong to one of the five largest banking groups in Italy; b) are the entities specialized in SME lending within a banking group; c) are organized in divisions; and d) have a higher number of hierarchical layers. It is important to notice that while the results presented in Table 7 above capture the average behavior of the bank – for example, if banks belonging to one of the five largest banking groups in Italy cut credit relatively more than others – the results in Table 8 show that these banks cut credit relatively more to smaller firms.

Table 8 - Change in credit supply, bank characteristics and firm size

Interaction of bank characteristic in each panel with:	Five largest banking groups (dummy) (1)	Credit cooperative banks (dummy) (2)	Bank specialized SMEs (dummy) (3)	Bank geo. coverage (dummy) (4)	Bank organized with divisions (dummy) (5)	Bank hierarc. levels (6)	Bank using scoring techniques (dummy) (7)
Small firms	-0.401***	-0.146	-0.887***	-0.137	-0.293**	-0.389**	-0.320
(1° quartile dummy)	(0.048)	(0.503)	(0.243)	(0.147)	(0.137)	(0.167)	(0.209)
Small to med. firms	-0.407***	-0.0545	-0.650***	-0.152	-0.403***	-0.487***	-0.530***
(2° quartile dummy)	(0.045)	(0.487)	(0.204)	(0.129)	(0.124)	(0.153)	(0.188)
Medium firms	-0.197	-0.482	-0.239	0.0270	-0.143	-0.112	-0.152
(3° quartile dummy)	(0.046)	(0.508)	(0.211)	(0.131)	(0.126)	(0.156)	(0.183)
Share of bank lines of	-1.954***	-1.941***	-1.970***	-2.079***	-2.191***	-2.085***	-2.216***
credit with the firm	(0.233)	(0.233)	(0.286)	(0.251)	(0.246)	(0.252)	(0.248)
Interest rate on bank	0.00432	0.00385	-0.00352	-0.00516	-0.000583	-0.00561	-0.00118
credit line	(0.00895)	(0.00795)	(0.00876)	(0.00836)	(0.00827)	(0.00838)	(0.00828)
Number of observations	11,073	11,073	8,072	9,717	10,211	9,629	10,258
adj. R-sq	0.319	0.318	0.271	0.247	0.320	0.249	0.319

Taken together, these results confirm therefore that smaller firms experienced a stronger reduction in credit supply precisely from those banks that have an internal organization that is less suitable to the transfer of soft information, because they are large, and they are organized in divisions and with a large number of hierarchical layers. Interestingly, these results also show that while banks that are specialized in SME lending within a banking group cut credit relatively less than others, they still reduced their credit supply relatively more to smaller firms. On the contrary, there is no evidence that credit cooperative banks reduced their credit supply differently depending on firm size, and there is only weak evidence that bank using credit scoring techniques cut credit relatively more to smaller firms.

Tables 9 and 10 present the results of the same specification of equation (3), controlling for two firm characteristics that are typically part of any loan dossier, and indeed can be transmitted without much effort even within banks with rather complex organizations: riskiness and profitability. As we have already argued above, both information are easily available, since they are collected and produced by a consortium that includes among others all the major Italian commercial banks.

Table 9 - Change in credit supply, bank characteristics and firm riskiness

Interaction of bank characteristic in each panel with:	Five largest banking groups (dummy) (1)	Credit cooperative banks (dummy) (2)	Bank specialized SMEs (dummy) (3)	Bank geo. coverage (dummy) (4)	Bank organized with divisions (dummy) (5)	Bank hierarchical levels (6)	Bank using scoring techniques (dummy) (7)
High risk firms	0.0663	0.558**	-0.215	0.102	0.120	0.190	0.00950
	(0.105)	(0.282)	(0.178)	(0.126)	(0.110)	(0.142)	(0.182)
Medium risk firms	0.0424	-0.0381	0.214	0.212**	0.0864	0.0205	0.116
	(0.0807)	(0.210)	(0.156)	(0.094)	(0.0846)	(0.106)	(0.135)
Share of bank lines of credit of the firm	-1.936***	-1.935***	-1.969***	-2.075***	-2.183***	-2.083***	-2.203***
	(0.233)	(0.233)	(0.286)	(0.251)	(0.246)	(0.252)	(0.248)
Interest rate on bank lines of credit	0.00382	0.00391	-0.00417	-0.00528	-0.00124	-0.00603	-0.00113
	(0.00795)	(0.00795)	(0.00875)	(0.00834)	(0.00829)	(0.00841)	(0.00827)
Number of observations	11,073	11,073	8,072	9,717	10,211	9,629	10,258
adj. R-sq	0.318	0.318	0.269	0.247	0.319	0.248	0.319

Indeed, Tables 9 and 10 do not show any identifiable pattern in the change in credit supply according to characteristics of the organization structure of the bank and the profitability and riskiness of the borrowers. This provides convincing evidence that this information is treated differently by banks with different organizations.

Table 10 - Change in credit supply, bank characteristics and firm profitability

Interaction of bank characteristic in each panel with:	Five largest banking groups (dummy) (1)	Credit cooperative banks (dummy) (2)	Bank specialized SMEs (dummy) (3)	Bank geo. coverage (dummy) (4)	Bank organized with divisions (dummy) (5)	Bank hierarchical levels (6)	Bank using scoring techniques (dummy) (7)
Low profitability firms (1° quartile dummy)	0.0154	0.421	-0.138	0.0620	-0.0447	-0.106	-0.0552
	(0.105)	(0.320)	(0.217)	(0.126)	(0.114)	(0.147)	(0.216)
Low to med. prof. firms (2° quartile dummy)	-0.102	0.643*	-0.0388	-0.0524	-0.196*	-0.0836	-0.0107
	(0.101)	(0.347)	(0.201)	(0.120)	(0.108)	(0.138)	(0.198)
Medium prof. firms (3° quartile dummy)	-0.104	0.367	-0.00223	-0.0332	-0.191*	-0.224*	0.0734
	(0.099)	(0.299)	(0.189)	(0.115)	(0.105)	(0.135)	(0.195)
Share of bank lines of credit of the firm	-1.939***	-1.934***	-1.962***	-2.076***	-2.185***	-2.083***	-2.202***
	(0.233)	(0.233)	(0.285)	(0.251)	(0.246)	(0.252)	(0.226)
Interest rate on bank credit line	0.00365	0.00400	-0.00423	-0.00525	-0.00113	-0.00573	-0.00114
	(0.00795)	(0.00795)	(0.00876)	(0.00835)	(0.00829)	(0.00840)	(0.00774)
Number of observations	11,073	11,073	8,072	9,717	10,211	9,629	10,258
adj. R-sq	0.318	0.318	0.268	0.246	0.319	0.248	0.319

4.5 Productivity and bank organization structures

Other firm characteristics in addition to size, profitability and a synthetic measure of riskiness can provide relevant information for a bank deciding whether to extend a bank loan. One such information is firm's productivity: more productive firms are more likely to survive in a competitive environment and therefore are less likely to default.

Indeed, higher productivity increases the profitability of a firm, and in turn its likelihood to remain in the market. Table 11 presents the results of a panel regression using the entire sample of firms of our analysis between 1992 and 2007, where the dependent variable is profitability, measured by returns on assets, and the main explanatory variable is lagged productivity, plus a number of controls that include lagged returns on assets, leverage, and a set of dummies for the class of credit risk. In addition, all regressions include dummies controlling for firm size, industry sector, regional location and time. The positive and highly statistically significant coefficient of our measure of total factor productivity in all the specifications provides strong evidence that productivity is a reliable predictor of profitability at the 1, 3 and 5 year horizons, even controlling for credit risk.

Table 11 – Profitability and total factor productivity

	Returns on assets (t+1) (1)	Returns on assets (t+3) (2)	Returns on assets (t+5) (3)
ROA_t	0.453***	0.230***	0.165***
ROA_{t-1}	0.106***	0.113***	0.118**
ROA_{t-2}	0.085***	0.063***	0.061**
TFP	0.014***	0.021***	0.021***
Leverage	0.001	0.001	-0.001*
Credit risk dummies	yes	yes	Yes
Size, Sector and year dummies	yes	yes	Yes
No. obs.	11,344	7,487	5,001

Collecting and processing information on firm productivity may be difficult, and indeed this is unlikely to be part of the standard hard information that is recorded in a loan dossier. However, it is plausible to assume that a carefully conducted analysis, possibly based also on soft information, is capable of better assessing what the overall efficiency of a firm is, and this is a feature very close to our notion of productivity. For this reason we argue that banks that lend more to firms with higher productivity are better at screening and monitoring their clients. We have already verified that, *ceteris paribus*, more productive firms experienced a smaller reduction in credit supply than less productive firms in the aftermath of Lehman's default. But given the focus of our analysis, it is interesting to investigate if banks with different organization structures assign an equal value to this measure.

The results presented in Table 12 provide some support to the hypothesis that banks with some types of organization structure are better than others at sorting out high-risk-high-productivity firms.

Table 12 - Change in credit supply, bank characteristics and firm productivity

Interaction of bank characteristic in each panel with:	Five largest banking groups (dummy) (1)	Credit cooperative banks (dummy) (2)	Bank specialized SMEs (dummy) (3)	Bank geo. coverage (dummy) (4)	Bank organized with divisions (dummy) (5)	Bank hierarchical levels (6)	Bank using scoring techniques (dummy) (7)
Low productivity firms	-0.106	0.243	-0.0970	-0.133	-0.180	0.0297	-0.0431
(1° quartile dummy)	(0.110)	(0.270)	(0.233)	(0.125)	(0.118)	(0.141)	(0.197)
Low to med. prod. firms	-0.251***	-0.0770	-0.326*	-0.0507	-0.228**	-0.312**	-0.130
(2° quartile dummy)	(0.094)	(0.266)	(0.184)	(0.111)	(0.098)	(0.129)	(0.157)
Medium prod. firms	-0.109	-0.169	-0.100	0.0199	-0.107	-0.183	-0.0450
(3° quartile dummy)	(0.088)	(0.219)	(0.178)	(0.104)	(0.093)	(0.118)	(0.145)
Share of total bank	-1.940***	-1.941***	-1.950***	-2.076***	-2.195***	-2.083***	-2.207***
lines of credit of the firm	(0.225)	(0.235)	(0.287)	(0.252)	(0.247)	(0.254)	(0.249)
Interest rate on bank	0.00338	0.00340	-0.00523	-0.00569	-0.00136	-0.00621	-0.00170
Credit line	(0.00796)	(0.00795)	(0.00874)	(0.00834)	(0.00831)	(0.00840)	(0.00828)
Number of observations	11,060	11,060	8,063	9,705	10,198	9,617	10,245
adj. R-sq	0.318	0.318	0.269	0.247	0.319	0.248	0.319

Although much fewer coefficients are statistically significant than in the case of firm size, all of them are negative, suggesting that banks are relatively more likely to cut credit to firms that have a lower level of productivity if they: a) belong to one of the five largest banking groups in Italy; b) are the entities specialized in SME lending within a banking group; c) are organized in divisions; and d) have a higher number of hierarchical layers. In fact, these are the same bank characteristics that have a statistically significant impact in affecting credit supply to firms of different size. We find no significant effect in the case of firms with very low levels of productivity, but this can be due to the higher variability of all characteristics referred to smaller firms: in fact, in a number of cases, the estimated coefficient is larger than that of larger firms, but the standard error of the estimate is very high.

The evidence presented in Table 12 suggests that total factor productivity may provide significant additional information with respect to riskiness to forecast future profitability. In a downturn of the scale experienced after Lehman's default, the ability to sort out firms with adequate prospects of survival from those with fewer probabilities can be extremely valuable, for the single firm as well as for the entire economy. To assess whether some banks have assigned higher value to information related to productivity, for given riskiness, we have singled out firms with high riskiness and high productivity. These have been defined as those firms with a level of the Z-score in the 6-9 range and a level of total factor productivity above the median. Our identification hypothesis is that banks with an organizational structure better able to assess their borrowers, as signalled by the fact that they do not penalize those with higher risk as long as they are at the same time more productive, and at the same time have the means and willingness to help them to recover from a temporary shock, should have a more lenient credit supply policy than other banks.

The results reported in Table 13 show that larger banks are more willing to grant loans to high-risk-high-productivity firms.

Table 13 - Change in credit supply, bank characteristics, firm riskiness and productivity

Interaction of bank organization characteristics in each panel with the high-risk-high-productivity firms dummy	Bank total assets (log) (1)	Five largest banking groups (dummy) (2)	Credit coop. banks (dummy) (3)	Bank specialized SMEs (dummy) (4)	Bank geo. coverage (dummy) (5)	Bank organized with divisions (dummy) (6)	Bank hier. levels (7)	Bank using scoring techn. (dummy) (8)
Risky-prod.	0,0507**	0,0298	-0,488**	0.317**	0,140*	0,101	-0,0138	0,0805
firms (dummy)	(0,0260)	(0,0710)	(0,251)	(0.140)	(0,0830)	(0,0751)	(0,0939)	(0,122)
Share of credit	-1,946***	-1,937***	-1,940***	-1.961***	-2,074***	-2,189***	-2,079***	-2,202***
to the firm	(0,233)	(0,233)	(0,233)	(0.282)	(0,251)	(0,245)	(0,252)	(0,247)
Interest rate on	0,00403	0,00386	0,00401	-0.00415	-0,00539	-0,00111	-0,00593	-0,00120
line of credit	(0,00795)	(0,00795)	(0,00795)	(0.00875)	(0,00836)	(0,00830)	(0,00840)	(0,00827)
No. of obs.	11,073	11,073	11,073	8,072	9,717	10,211	9,629	10,258
adj. R-sq	0.318	0.318	0.318	0.269	0.247	0.319	0.248	0.319

This depends on two facts. First, as shown in Panel (3), credit cooperatives, that are very small banks, are significantly less likely than other banks to grant loans to high-risk-high-productivity firms. Second, as shown in Panel (4), financial intermediaries within larger banking groups that are specialized in SME lending are significantly more likely to grant loans to high-risk-high-productivity firms. In addition, Panel (5) shown that banks with a larger geographical presence also granted relatively more credit to high-risk-high-productivity firms. All other characteristics of bank's organization have no significant effect.

These results, together with those of Table 12, provide a rather mixed picture. Large banks and entities specialized in SME lending appear to make less use of information capable of assessing the overall productivity of their borrowers. However, they prove to be better than others to help those firms that are in temporary difficulty but have a higher probability of surviving a crisis, because their have higher productivity.

4.6 Robustness checks

Our baseline analysis focuses on extended credit lines, that provide the best measure of changes in bank credit supply. In fact, changes in amounts used by firms partly reflect the fact that borrowers in need can pull from the credit lines that they have already been granted. Despite the fact that extended credit lines are a better measure, in a set of regression available upon request we have verified that the results of our baseline specification are broadly confirmed if we use the ratio of the change in used credit lines to firm total assets as dependent variable when estimating specifications (1)-(3). Indeed, this is not surprising, given the high correlation between changes in extended credit lines and used credit lines in Table 5. Still, it provides additional evidence of the robustness of our findings that bank organization has an impact on how they react to exogenous shocks, and how this can be different depending on some characteristics of the borrowers.

Next, we verified whether another dimension of bank credit supply changed in the aftermath of Lehman's default – namely the interest rate charged on bank lines of credit – and to what extent the changes were different depending on the characteristics of the lenders and of the borrowers. Indeed, Table 2 shows that banks slightly reduced the interest rate charged on credit lines, the more so for larger firms. The results of the econometric analysis, that are also available from the authors upon request, confirms the evidence of the descriptive statistics also controlling for other characteristics of the borrowers. However, we find no evidence that the organization structure of the banks has a significant impact on the changes in the interest rates that it charges. Neither that the organization of the bank impacts differently on the changes in the interest rates charged to firms with different characteristics.

Overall, the results of the robustness checks provide additional evidence confirming that bank organization impacts loan supply, but only on the availability of credit and not on its cost.

5. Conclusion

The 2007-2008 financial crisis, and in particular the shock to banking markets caused by Lehman's default in September 2008 raised a number of fundamental questions on the impact of bank organization and business models on credit supply. Much has been learnt on how banks reacted to the crisis and how this has impacted on borrowing firms and ultimately on the real economy.

In this paper we have added one dimension to the analysis, focusing on the role of bank organization. A large anecdotal evidence argues that large banks – that adopt standardized lending techniques and are less capable of processing and benefiting from soft information – cut credit supply relatively more. Merging high quality bank-firm data with information on bank organization structure, we have verified to what extent the anecdotal evidence survives to a more rigorous empirical analysis.

While thoroughly controlling for credit demand by exploiting the presence of multiple lending relationships to include in the econometric specification borrowers' fixed effects, we have found some evidence that, during the crisis caused by Lehman's default, banks with internal organization that allow for a better use of soft information – because they have a smaller number of hierarchical levels and are specialized in lending to smaller, and typically more opaque firms – granted relatively more lines of credit than other banks. More importantly, we have found robust evidence that smaller firms experienced a stronger reduction in credit supply from those same banks that have an internal organization that is less suitable to the transfer of soft information. However, we also find that banks with specific organizations devoted to SME lending reduced their credit supply relatively less than other banks to firms that showed short term problems but better longer term prospects, because they had high risk but also high productivity. Finally, we find no significant effect of bank organization on the changes in the interest rates charged on bank lines of credit.

References

Albertazzi, U., and Marchetti, D. Jr. (2010). Credit Crunch, Bank Size and Borrower Quality: An Analysis of Bank-Firm Relationships after Lehman, mimeo, Bank of Italy.

Alessandrini, P., Presbitero, A. F., Zazzaro, A. (2010). Bank size or distance: what hampers innovation adoption by SMEs?, Journal of Economic Geography 10, 845-881.

Alessandrini, P., Presbitero, A. F., Zazzaro, A. (2009). Banks, distances and firms' financing constraints, Review of Finance 13, 261-307.

Altman, E.I., (1968). Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy, Journal of Finance 23, 589-609.

Altman, E.I., Marco, G., Varetto, F. (1994). Corporate distress diagnosis: Comparisons using linear discriminant analysis and neural networks (the Italian Experience), Journal of Banking and Finance 18, 505-529.

Berger, A. N., Miller, N. H., Petersen, M. A., Rajan, R. G., & Stein, J. C. (2005). Does function follow organizational form? Evidence from the lending practices of large and small banks. Journal of Financial economics, 76(2), 237-269.

Berger, A.N., and Udell, G., (2006). A More Complete Conceptual Framework for SME finance, Journal of Banking Finance 30, 2945-2966.

Bonaccorsi di Patti, E. B., Sette, E. (2016). Did the securitization market freeze affect bank lending during the financial crisis? Evidence from a credit register, Journal of Financial Intermediation 25, 54-76.

Cingano, F., Manaresi, F., Sette, E. (2016). Does Credit Crunch Investment Down? New Evidence on the Real Effects of the Bank-Lending Channel, Review of Financial Studies 29, 2737-2773.

Detragiache, E., Garella, P., Guiso, L. (2000). Multiple versus single banking relationships: Theory and evidence, Journal of Finance 55, 1133-1161.

DeYoung, R. (2015). How relationships can reduce risk in small business lending. European Economy - Bank Regulation and the Real Sector 2, 87-99.

DeYoung, R., Gron, A., Torna, G., Winton, A. (2015). Risk overhang and loan portfolio decisions: small business loan supply before and during the financial crisis, Journal of Finance 70, 2451-2488.

Gambacorta, L., Mistrulli, P. E. (2014). Bank heterogeneity and interest rate setting: what lessons have we learned since Lehman Brothers?, Journal of Money, Credit and Banking 46, 753-778.

Khwaja, A. I., Mian, A. (2008). Tracing the impact of bank liquidity shocks: Evidence from an emerging market, American Economic Review 98, 1413-1442.

Klette, T. J., Griliches, Z. (1996). The Inconsistency of Common Scale Estimators when Output Prices Are Unobserved and Endogenous, Journal of Applied Econometrics 11, 343-361.

Levinsohn, J., Petrin, A. (2003). Estimating Production Functions Using Inputs to Control for Unobservables, Review of Economic Studies 70, 317-341.

Liberti, J. M., Mian, A. R. (2009). Estimating the effect of hierarchies on information use, Review of financial studies 22, 4057-4090.

Melitz, M. (2000), Estimating Firm-Level Productivity in Differentiated Product Industry, Harvard University, mimeo.

Olley, G.S., Pakes, A. (1996). The Dynamics of Productivity in the Telecommunications Equipment Industry, Econometrica 64, 1263-1297.

Del Prete, S., Pagnini, M., Rossi, P., Vacca, V. (2017). Lending organization and credit supply during the 2008–2009 crisis. Economic Notes, 46, 207-236.

Stein, J. C. (2002). Information production and capital allocation: Decentralized versus hierarchical firms, Journal of Finance 57, 1891-1921.

Udell, G., 2009. How Will a Credit Crunch Aﬀect Small Business Finance? RBSF Economic Letter, 2009-09, Federal Reserve Bank of San Francisco (March 6).

Udell, G. F. (2015). Issues in SME access to finance. European Economy - Bank Regulation and the Real Sector 2, 61-74.