Does your neighbour know you better?

The supportive role of local banks in the financial crisis

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Abstract. Relationship lending allows local banks to collect private information about their customers and to mitigate information asymmetries that often lead to credit rationing. In this paper, we argue that soft information collected through relationship lending favors lending decisions even when borrowers' quality is poor from a "hard-information" perspective. We compare the behavior of local versus non-local banks using data before and after the Great Recession. We exploit the heterogeneity in banks' reliance on soft information to study how their lending strategies changed when firms' hard-information indicators deteriorated after the outbreak of the financial crisis. Our paper shows that firms predominantly funded by local banks reported lower credit rationing during the Great Recession. Local banks were also less likely to terminate existing relationships with their customers during the financial crisis, suggesting that they continued funding their clients even when borrowers' balance sheet variables worsened. We rule out alternative hypotheses explaining our results, such as demand effects, "zombie-lending" behavior, or different impacts the financial crisis had on the credit supply of local versus local firms. This leads us to conclude that thanks to their greater reliance on soft information, local lenders supported their customers to a higher extent during bad times.

JEL Classification: G21, G30, F34.

Key Words: Local Banks, Soft Information, Relationship Lending, Financial Crisis, Credit Rationing

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1. Introduction

Local banks play a crucial role in funding small and opaque businesses. A number of studies have shown that the geographical proximity between banks and firms affects the way information is processed and collected and, in turn, how credit is made available (e.g. Petersen and Rajan, 2002; Stein, 2005). The personal relationship local bankers establish with funded entrepreneurs – known in the literature as "relationship lending" – allows lenders to acquire private, "soft" information from their clients. This relates, among others, to the quality of borrowers' managerial practices, their relationships with suppliers and customers, and their impact on the local economy (Berger, 1999; Berger and Udell, 2002; Petersen, 2004).

Owning soft information helps lenders mitigate information asymmetries in credit markets, which often lead to credit rationing, as shown in the seminal paper by Stiglitz and Weiss (1981). Thanks to soft information, small and opaque firms are able to receive funding even in absence of public, "hard" information (e.g. Berger and Udell, 1995; DeYoung et al., 2004).

Against this background, a related question is which role soft information plays when hard information exists, but it suggests that borrowers have poor quality. In particular, how do banks take their lending decisions when borrowers' hard-information credit assessment suddenly becomes discouraging? This paper shows that soft information can lead local lenders to grant credit when hard information would suggest the opposite.

From a theoretical perspective, if a firm's "hard-information" profile looks poor, local banks might grant credit to this firm as long as soft information reveals that the borrower's quality is good. In such cases soft information may work as a substitute for hard information in lending decisions.

On the contrary, non-local lenders build their lending decisions mostly on hard information. As a consequence, if the borrower's "hard-information" quality is not satisfactory, these banks might deny credit without resorting to soft information to validate – or change – such assessment.

We test these predictions using a novel dataset of loans granted by 348 Italian banks to a representative sample of 2,373 Italian firms in the years 2007 and 2008. This period coincides with the year immediately before and after the collapse of Lehman Brothers, which took place in September 2008. These data allow us to distinguish between local and non-local banks and to relate banks' lending strategies to banks' characteristics – and to those of their borrowers – before and after the financial crisis.

Our identification strategy exploits the heterogeneity in banks' reliance on relationship lending to study the lending strategies of local versus non-local banks before and after the outburst of the Great Recession. It builds on two assumptions: first, local banks use soft information to a higher extent than non-local banks (e.g. Agarwal and Hauswald, 2010), but they rely on hard information to a similar extent. Second, firms' hard-information indicators became unexpectedly worse in the period immediately after the outbreak of the financial crisis – but not necessarily their soft-information profile.[1] In order to account for credit demand, we only select and include in the analysis firms that borrowed from both local and non-local firms, the year before the crisis. This allows us to control for any potential selection effect in the pool of firms funded by local versus non-local banks, and to neutralize any differential impact the financial crisis had on firms relying on local versus non-local credit.[2]

Our hypothesis is that despite firms' hard-information outlook was negatively affected by the outburst of the financial crisis, local banks were able to identify and fund creditworthy firms through their soft-information "screening". Thus, any difference in lending across local and non-local banks to the *same* set of firms, once firms' hard-information indicators deteriorated in 2008, should be precisely driven by banks' different reliance and use of relationship lending. This is

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[1] We will discuss extensively how firms' balance sheet worsened after the financial crisis spread in Section 5.
[2] We thank an anonymous referee for pointing this out.

unless the financial crisis hit local and non-local banks in a different way – which we find not being the case.

In line with our predictions, our main finding is that firms borrowing from local banks reported lower rate of credit rationing in 2008 than firms borrowing from non-local banks. This result is robust after controlling for the characteristics of the bank-firm relationship, banks' balance sheet variables, as well as firms' characteristics. It also holds after controlling for a set of firms' balance sheet indicators, suggesting that firms' "unobservable" traits – those that can only be captured through relationship lending – play a significant role in explaining lenders' supply decisions.

To explore the mechanism underlying this result, we look at the extensive margin of credit and find that local banks were less likely than non-local banks to terminate existing relationships with their customers during the financial crisis. Conditional on a relationship being already in place when hard-information indicators were good, local banks were less likely to cut such relationship as hard-information indicators became poorer. Assuming that all banks act rationally – i.e. they are profit maximizers – this suggests that local banks were able to leverage on soft information to identify good customers.

Taken together, our findings show that relationship lending plays a crucial role in banks' lending decisions. Thanks to soft information, local banks kept funding their customers to a higher extent than non-local lenders when hard-information indicators suddenly worsened. One *caveat* to our results is that to precisely account for the role of hard versus soft information, we only look at the evolution of firm-bank relationships conditional on them being already in place before the outbreak of the Great Recession, when hard-information indicators were still satisfactory. On the contrary, we cannot speak to changes in banks' lending decisions – and to the role of soft information – towards firms whose hard-information outlook had always been unsatisfactory.

To complete our analysis, we rule out competing hypotheses that might explain our results. In fact, a natural question is whether our findings are driven by local lenders adopting a "zombie lending" strategy (Peek and Rosengren, 2005; Albertazzi and Marchetti, 2010), rather than funding creditworthy customers identified through soft information. Under this view, local banks, which are usually small in size and also less capitalized, might have kept lending to firms they had high credit exposure to even during financial crises. This is in order to avoid that such firms, once in financial distress, may have compromised the banks' stability. If this were the case, we should observe local banks to be less likely to terminate existing relationships with firms with worse balance sheet characteristics or with firms holding relatively high credit shares during the financial crisis. This hypothesis is however not confirmed in the data. In addition, one may wonder whether our results are driven by a different impact of the financial crisis of local versus non-local banks, rather than by differences in lenders' reliance on soft information. Because of their nature, local banks might have been subject to less strict regulatory requirements during the financial crisis, thus generating differences in the liquidity provision of local versus non-local banks. We study the intensive margin of credit and we find that local and non-local banks did not differently experience credit contraction resulting from the Great Recession.

All in all, our results show that local lenders, who make a larger use of soft information through relationship lending, tightened their credit supply to a lower extent than non-local banks. They did so especially when hard-information revealed a poorer firms' outlook. Our findings suggest that soft-information can substitute hard information, and can help lenders make better-informed lending decisions. When it is used, as it is the case for local banks, firms experience greater credit stability, even in periods when their balance sheet characteristics significantly worsened.

Our paper contributes to the literature on soft information and local banks, along several dimensions. First, it focuses on the role of relationship lending, in a similar spirit as Liberti (2003; 2005) and of Liberti and Mian (2009). Second, it looks at the importance of soft information for small business funding, particularly in periods of financial downturns. For instance, Gobbi and Sette (2013) show that, after Lehman Brothers' default, firms benefited from closer bank lending relationships, both in terms of credit growth and interest rates. In a similar spirit, Gambacorta and Mistrulli (2011) document that close lending relationships were effective in insulating firms from the financial crisis as their borrowing costs increased less than those of other firms. Presbitero et al. (2014) find that in credit markets with a stronger presence of functionally close banks, large, good-quality firms have experienced less credit tightening than in functionally distant credit markets.

Our paper also contributes to the literature that studies how to identify and measure soft information. Garcia-Appendini (2011) takes an "indirect" approach and shows that banks rely to a lower extent on public credit registries when they have access to soft information. In a similar spirit, Cerqueiro, Degryse and Ongena (2010) look at residuals in regressions with public credit information to quantify soft information.

Finally, from a policy perspective, our results highlight the importance of local banks for small business funding, even during financial turmoils, and suggest that governments and central bankers should encourage the deepening of outreach of local financial intermediaries, as they prove to be important buffers against negative shocks for firms.

The paper is organized as follows: Section 2 discusses the theoretical framework our identification strategy builds on. Section 3 focuses on local banks and their characteristics; in Section 4 we present the data and descriptive statistics. In Section 5 we illustrate results from our analysis. Robustness checks are discussed in Section 6. Section 7 concludes.

2. Theoretical framework

Our identification strategy can be explained by a simple two-period theoretical model where firms have two sets of characteristics: the first one can be observed through public, hard-information, like firms' balance sheets, financial statements, and credit registries. The second set of characteristics is private, and it is only observable through soft information gathered with relationship lending. Observing hard information is costless: therefore, banks always look at hard information first to decide whether or not to grant credit to a firm. On the contrary, banks face different costs in using soft-information: this cost is lower for local than for non-local banks, precisely because of relationship lending.

In period one, hard information suggests that the quality of the firm is high: soft information provides a similar assessment. In fact, it is reasonable to think that if the firm has high productivity, rarely the management practices adopted are bad.

In period two, hard information worsens, but not necessarily soft information worsens, too. This is especially true if the causes of hard-information deterioration are not firm-specific, but rather systemic – as it was the case for the Great Recession.[3]

In period one, when hard information is good, banks always lend.[4] On the contrary, in period two, when hard information becomes worse, lenders have to decide whether or not they want to acquire soft information to achieve additional information on the firm's quality, or just turn down the funding request. In taking this decision, banks have to consider two elements: the cost of acquiring soft information, and customers' "turnover" – i.e. the rate at which they can meet new customers.

Not only banks differ in terms of costs to access soft information, but also in the demand for funds. While non-local banks face an untapped demand for funds, local banks face a limited demand for loans. Local banks usually operate in a smaller set of credit markets, compared with non-local banks. If the quality of firms in the pool is low from a hard-information point of view, local banks may encounter the risk of not using all their funds, should they turn down all loan

[3] For instance, while firms' productivity or employment can significantly worsen during financial downturns, it is hard to imagine that an entrepreneur would adopt worse managerial practices, or that cultural norms would change during financial crises.

[4] We assume that lending is always preferred to non-lending.

requests from bad "hard-information" borrowers. As lending is always preferred to non-lending, they will therefore decide to bear the cost of collecting soft-information as long as they can bear this cost.[5] A corollary to this is that the smaller the outreach of a bank, the higher is the likelihood it will engage in the collection of soft information. Non-local banks, instead, cater to a much larger number of firms. If a firm appears not worth funding, they will just drop its application and screen the next one. In light of this discussion, we make the following testable predictions:

Prediction 1: *When a firm's quality is good from a hard-information perspective, all banks will lend, irrespectively of their reliance on soft information.*

Prediction 2: *As the quality of a firm worsens, only banks that rely on soft information will keep lending to this firm, as long as soft information reveals that the firm's quality is good.*

Our data consists in the universe of loans that a panel of 2,373 Italian firms received from 348 Italian banks in 2007 and 2008. All these firms borrowed from both local and non-local banks, both before and after outbreak of the financial crisis. Since these firms received credit before the crisis by non-local banks – who mostly rely on hard information to make lending decisions – this suggests that their hard-information indicators before the financial crisis were good – or good enough to be funded. It follows that, for the above discussion, also their soft-information quality was good, as well. The unanticipated outbreak of the financial crisis thus allows us to study to what extent this sample of firms, which were good *ex-ante* – both from a hard-information and a soft-information point of view – received funding from local versus non-local banks once their hard-

[5] Still, local banks will lend only if soft information suggests that the borrower's quality is high.

information indicators worsened, conditional on their soft-information quality still remaining good.[6]

3. Measuring bank localism

In this paragraph we discuss how we define local banks and how we use such categorization in our analysis. Bank localism can be described by a set of characteristics – e.g. narrow geographical outreach, simple organizational structure – that allow local lenders to have a stronger bond with the local economy than non-local banks. The existing literature has in fact identified local banks as financial institutions either with fewer managerial levels (Berg and Udell, 2002), or that are geographically concentrated in few local credit markets (Hannan and Prager, 2004; Hannan 2006), or with relatively short distances between the headquarter and the branches (Alessandrini et al., 2010; Jiménez et al., 2009). In contrast with these papers, we introduce a novel measure of bank localism that takes simultaneously into account banks' geographical concentration in local credit markets, and the relative size – in terms of volume of credit – of these markets.

The underlying idea is that, to be classified as local, not only banks should be concentrated in fewer local credit markets, but these markets should be relative small – local banks should be the main lenders in those markets. It is precisely through their relative importance for a certain credit market that local banks can collect soft information to a higher extent than non-local banks. Think of a bank that operates in very few small-size credit markets. This bank will probably lend to firms that are connected among each other because they belong to the same supply chain or industrial cluster. This, in turn, allows this bank to play a key role in those markets, and to gather a detailed understanding of the economic, but also of the social and cultural context it operates in. Such bank corresponds exactly to a local bank.

[6] As we already discussed, it is reasonable to assume that borrowers' characteristics that can be identified through relationship lending are unlikely to be correlated with a financial crisis, and less so in a negative way.

Our measure of bank localism is built matching different data sources: first, the Italian Credit Register, which contains information on the volumes of credit each bank lends to each firm. Second, the 2001 Italian National Census carried out by the Italian National Statistics Institute (ISTAT), which identifies 686 Local Labour Market Areas (LLMAs) throughout the Italian territory.[7] This is used to relate each firm's municipality to its corresponding LLMAs, and to calculate the amount credit lent by banks in each LLMA.[8]

Our measure of localism consists in a simplified version of Williams' index, which was first used to study firms' specialization across local labour market areas (Williams, 1991).[9] The index is constructed at the bank level, is time variant, and identifies the extent to which a bank j in year t that operates in $k=1,2,\ldots,m$ LLMAs is local, based on the volumes of credit lent in each of those LLMAs. It is computed as follows:

$$local_{jt} = \sum_{k=1}^{m} \left(\frac{c_{jkt}}{c_{jt}} - \frac{c_{kt}}{c_t} \right)^2 \tag{1}$$

where for all LLMAs where bank j operates in year t: i) c_{jkt} is the amount of credit bank j lends in LLMA k in year t; ii) c_{jt} is the total amount of credit lent by bank j in year t; iii) c_{kt} is the amount of credit borrowed in the LLMA k by all firms headquartered in LLMA k, and iv) c_t is the total amount of credit lent in year t.

According to such measure, a bank will be more local the higher is its credit concentration across fewer LLMAs, and the lower is the weight – in terms of credit volume – of these LLMAs on the

[7] Yet, firms in our dataset are spread across a lower number of LLMAs. Therefore, we end up with 419 LLMAs in our final dataset from the initial 686 LLMAs. LLMAs are defined as a set of adjacent municipalities linked by daily commuter flows for work purposes. More precisely, a LLMA "*is a cluster of municipalities whose self-containment in terms of commuting passes a minimum threshold* [in terms of number of residents and available jobs]" (Casado-Díaz, 2007).

[8] The adoption of LLMAs as a proxy for local credit markets allows us to capture very precisely the extent to which a bank operates in the territory. At the same time, LLMAs, because of their dimension and number, are able to incorporate much more variation than Italian provinces. In Italy, there were 107 provinces versus 686 LLMAs (data refer to 2010).

[9] Williams' index is used to classify firms into more or less specialized, according to both their production shares over one or several sub-markets and to the relative size of these sub-markets compared to the overall production market. Farabullini and Gobbi (2000) later apply this index to the Italian banking sector to define banks' degree of specialization. Their measure takes into account the number of local credit markets where banks operate (through loans, deposits, and bank offices), and the weight of these local credit markets on the national credit market. To the best of our knowledge, however, we are the first to adopt Williams' index to generate a measure of bank localism.

overall credit market. This measure ranges from zero to two: low levels of the index are associated with banks that spread their credit equally across local credit markets in accordance with their relative sizes – these banks are thus classified as non-local. High values of the index, on the contrary, identify local banks – those that tend to concentrate their credit over smaller local credit markets. Further details on the index are provided in Appendix C.

Compared to the existing measures of bank localism, our index includes two novel aspects: First, banks' geographical concentration is defined not only based on the number of credit markets where a bank operates, but also on the volume of credit disbursed in those markets. In this sense, our index takes into account the level of bank competition in terms of loans at the local credit market level. A bank that operates in more than one local credit market may be local or not depending on the relative size of these markets with respect to the overall Italian credit market. Second, our measure has the advantage of evaluating the importance of each bank in every single market, thus going beyond the mere bank-size dimension, traditionally considered as a key aspect for localism. For instance, a bank that is classified as small according to the dimensional criterion, not necessarily will be local.

Appendix C discusses to what extent our definition of bank localism correlates with bank size, using asset-based categories from Bank of Italy. Interestingly, we find that one Italian bank – big in terms of assets, which would have been defined as non-local, according to the dimensional criterion – displays a high degree of localism. Conversely, not all small banks in our dataset are classified as local. This suggests that bank localism, as per our index, does not fully coincide with bank size. In the next sections, we will discuss in detail how these two measures relate and contribute to explain firms' credit rationing.

4. Data and Descriptive Statistics

4.1. Data

Our novel dataset is built from different sources. The first set of data is obtained from the Bank of Italy's survey of industrial and service firms with at least twenty workers (INVIND). This survey is carried out once a year on a stratified sample of Italian firms and contains unique questions designed to elicit information on their financing needs and the existence of credit rationing. We match the firms in the INVIND sample with the Italian Central Credit Register (*Centrale dei Rischi*). This dataset contains information on the credit borrowed by Italian non-financial firms to banks operating in Italy. Merging these two data sources allows us to assess every single loan amount borrowed by each firm in the INVIND survey from any bank operating in the Italian credit market. We then obtain firms' balance sheets information from the CERVED dataset, comprising official records filed with Italian Chambers of Commerce and reported by the Cerved Group. Finally, banks' characteristics are obtained from both Supervisory Reports and Bank of Italy Annual Reports. For each bank in the dataset, we classify them into local and non-local, based on the index we discussed in Section 3.[10] By matching these data sources, we end up with a panel 2,373 firms borrowing from 348 banks – both local and non-local – over the years 2007 and 2008.

4.2. Descriptive Statistics

Our dataset allows us to create a measure of credit rationing at the firm level. This is constructed using the unique information we obtain from the INVIND survey. We classify as

[10] Banks are classified as local or not local depending on whether their index of localism is above or below the median of the index distribution.

credit rationed firms that were in need of additional funds but stated that their funding request was turned down by the financial intermediaries they contacted.[11]

Table 1 summarises the characteristics of the firms and the banks in our sample, evaluated in 2007. Panel A shows that three per cent of firms reported experiencing credit rationing. This share is consistent with findings from other studies – ECB's SAFE survey in the EU countries,[12] or surveys conducted in France by Insee and OSEO.[13] In terms of balance sheet characteristics, firms are on average 42 years old and 63% of them has more than 50 employees. Consistent with these data, firms' average ROA is 1.469. Firms appear moderately risky: the average risk rating in our sample is 4.6 on a scale from 1 (very safe) to 9 (very risky). Panel B of Table 1 shows descriptive statistics for banks' variables. Banks' size is expressed as a discrete index going from 1 (major banks) to 7 (minor banks). The median bank's size in our sample is 5, revealing that half of the banks in our sample are small and minor banks. The average value of the index of localism, computed in Section 3, is 0.571.

In terms of relationship lending variables, Panel C of Table 1 shows that the median number of bank relationships for each firm is 7, suggesting that a large majority of Italian banks is engaged in multiple bank lending relationships. In addition, only 7% of the bank-firm relationships in place in 2006 were interrupted in 2007 suggesting that once formed, such relationships are pretty stable.

[11] Our measure of credit rationing is obtained by combining the outcomes of two separate questions of the INVIND survey: in the first question, firms were asked whether they needed more funding than what they had actually received; in the second, firms were asked whether the banks they addressed to receive more funding had eventually turned down their credit request. Answers to both questions are reported in binary form. Both questions are from Part 5 (Firm Funding) of the survey. The firms were asked to answer first to question V316 "*You should indicate if, given the firm's cost and collateral conditions, you ask for more debt load*"; then to question V267 "*Please indicate if the contacted financial intermediaries proved not to be willing to increase your funding volume*". We classify firms reporting a positive answer to both questions as financially constrained.
[12] Survey on the access to finance of SMEs in the euro area, available at http://www.ecb.int/stats/money/surveys/sme/html/index.en.html. We thank Denis Fougère and Patrick Sevestre for pointing this out.
[13] http://www.oseo.fr/notre mission/publications/etudes et rapports/generalistes.

5. Identification Strategy

Our identification strategy exploits the heterogeneity in banks' reliance on soft information to study the lending strategies of local versus non-local banks before and after the outburst of the Great Recession. It builds on the assumption that the extent to which banks use soft information positively correlates with their level of localism. If this assumption is confirmed, we should observe local banks to be more likely to fund small and opaque businesses than non-local banks. We test this prediction by estimating the following regression:

$$firm\ characteristic_{i,2007} = \beta_0 + \beta_1 \overline{local_{\iota,2007}} + \varepsilon_i \qquad (2)$$

Where $firm\ characteristic_{i,2007}$ is a set of firm-level variables – including size, age, profitability, riskiness assessment, and probability to report credit rationing – taken from both the INVIND and the CERVED dataset and evaluated the year before the financial crisis started. $\overline{local_{\iota,2007}}$ is the measure of bank localism constructed in (1), averaged at the firm level. This expresses the extent to which firms are funded by local versus non-local banks and it is computed as follows:

$$\overline{local_{\iota t}} = \sum_{j=1}^{n} \left(\frac{c_{ijt}}{c_{it}} * local_{jt} \right) \qquad (3)$$

that is, for all the banks that lend to firm *i* in year *t*, we take the weighted average of the banks' index of localism ($local_{jt}$), the weights being the share of credit borrowed by firm *i* from bank *j* in year *t* over the total amount of credit borrowed by firm *i* in year *t*.[14]

[14] We construct the weights using loan data from the Italian Credit Register.

In order to control for potential endogeneity, we use in (2) firms' characteristics evaluated before the outburst of the financial crisis. Results from equation (2) are shown in Table B1. Column (1) of Table B1 shows that the probability that firms report being credit rationed is not significantly different across firms funded by local versus non-local banks. This confirm **Prediction 1** we made in Section 2: When a firm's quality is good from a hard-information perspective – as it was the case before the financial crisis –, all banks will lend, irrespectively of their reliance on soft information. Consistent with our assumption, firms funded by local banks to a higher extent appear more opaque: in fact, they are on average significantly smaller, younger, and more leveraged. Interestingly, the overall risk assessment is slightly better for firms borrowing from local banks (Column 8 of table B1). Although the coefficient of $\overline{local_{i,2007}}$ is positive and significant in column 8, it is however small in magnitude, suggesting that firms borrowing from local versus non-local banks have very similar risk assessment.

Since we observe a potential selection issue for firms funded by local versus non-local banks, this further motivates the need to conduct our analysis only with firms that in 2007 borrowed from both local and non-local banks. This restricts our sample to 2,373 firms, thus dropping 5% of the firms from the initial sample as these were borrowing exclusively from either local or non-local banks.

5.1 Credit rationing during the Great Recession

Before turning to the main analysis, we study whether firms' characteristics worsened during the financial crisis. To this end, we estimate the following regression equation at the firm level:

$$firm\ characteristic_{i,t} = \beta_0 + \beta_1 crisis_t + \varphi_i + \varepsilon_{i,t} \tag{4}$$

where $firm\ characteristic_{i,t}$ is a set of firms' characteristics measured in year *t*, with *t*=2007;2008 and $crisis_t$ is a dummy that takes the value of zero in year 2007 and one in year

2008. φ_i are firms fixed effects. Results from equation (4) are shown in Table B2. In line with our hypotheses, firms' hard-information outlook became poorer once the Great Recession spread. The probability that firms report credit rationing almost doubled during the crisis, with 5.5% per cent of firms reporting credit rationing in 2008 versus less than 3% in 2007, as shown in Table 1. Moreover, during the crisis, firms' balance sheet indicators significantly worsened. Firms became on average less profitable and reported lower revenues. The average leverage however significantly decreased, potentially reflecting the increase in credit rationing.[15]

Keeping results from Table B2 in mind, we study whether firms reported a lower credit rationing from local banks than from non-local banks, during the financial crisis. Our hypothesis is that firms who received funding during periods of financial stability from both local and non-local banks – which is suggestive of good hard-information and soft-information indicators – should have experienced larger credit tightening during periods of financial downturns by non-local lenders. This is because during such times their hard-information outlook worsened and non-local banks might have found it too expensive to collect soft information to assess whether their existing customers were still worth funding. We use a Difference-in-Difference approach to compare the probability that firms with higher versus lower exposure toward local banks reports to be credit rationed across two periods, the year before and after the financial crisis. We estimate the following regression equation at the firm level:[16]

$$p(credrat)_{it} = \beta_0 + \beta_1 \overline{local_{\iota,2007}} + \beta_2 crisis_t + \beta_3 \left(\overline{local_{\iota,2007}} * crisis_t\right) + \varepsilon_{it} \tag{5}$$

where $p(credrat)_{it}$ is the probability that firm i reports having experienced credit rationing (derived from INVIND); $crisis_t$ is a dummy which takes the value of one in 2008 and zero otherwise, and $\overline{local_{\iota,2007}}$ is our measure of bank localism computed at the firm level, as shown in

[15] The leverage is indeed defined as debt over equity.

[16] This is because the self-reported measure of credit rationing obtained from INVIND is a firm-level variable.

(2).[17] We are particularly interested in the sign and the significance of β_3, the Diff-in-Diff coefficient. We use a probit model to estimate equation (5). Results are shown in Table 2. Column (1) shows the marginal effects of our estimates without adding controls. The coefficient of the interaction term $\overline{local_{\iota,2007}} * crisis_t$ is negative and significant, revealing that the higher is the firm's exposure towards local banks, the lower the likelihood to report having being credit rationed during the financial crisis. We include firms' and banks' controls in Column (2) and (3), respectively.[18] We include firms' age, size, leverage and rating, these variables being evaluated at baseline to control for any potential endogenous change in borrowers' quality precisely because of the financial crisis. We also include in the specification shown in column (2) the firm's number of bank lending relationships, again before the crisis. β_3 remains negative and significant. Finally, we include a set of banks' characteristics averaged at the firm level using an approach akin to how we computed $\overline{local_{\iota,2007}}$. This set of variables comprises banks' size, the share of loans not funded on the retail market and banks' capital ratio. β_3 is negative and significant even after including banks' size, confirming that our measure of localism captures a different dimension from banks' dimension.

All in all, Table 2 shows that, conditional on being funded by both local and non-local banks, firms reported a lower rate of credit rationing during the financial crisis the higher their reliance on local banks. These results are robust to the inclusion of both firms' and banks' variables. This confirms our hypothesis that when hard-information variables significantly worsened – as shown in Table B2 – lenders who rely on soft-information to a larger extent were less likely to curtail credit to firms.

[18] This is because we cannot estimate equation (5) including firms fixed effects. Estimates using a Linear Probability Model are available upon request.

5.2 Extensive margin of credit

The main result from Table 2 is that firms experienced a lower credit tightening during the financial crisis from lenders that rely on soft-information to a higher extent. The underlying intuition is that local banks keep funding their customers when hard-information worsens, precisely because they rely on soft-information to compensate for "bad" hard-information indicators.

To test this hypothesis, we use data from the Italian Credit Registry, which provides information on every loan borrowed by each firm in our sample. For each firm-bank relationship, we know in which year the loan was disbursed, its amount, and whether the lender for that particular loan was a local or non-local one, based on the definition we previously discussed.

This allows us to compute the extensive margin of credit and to study whether local lenders were indeed less likely than non-local ones to cut credit to their existing customers.

We estimate the following regression equation using a probit model:

$$p(terminate)_{ij2008} = \gamma_0 + \gamma_1 dlocal_{j2007} + \varepsilon_{ij} \tag{6}$$

where the dependent variable, $p(terminate)_{ij2008}$ is the probability that a lending relationship between firm *i* and bank *j* that existed in 2007 is terminated in 2008, and $dlocal_{j2007}$ is a dummy that takes the value of one if bank *j* is local and zero otherwise.[19] Results from equation (6) are shown in table 3, column (1). γ_1 is negative and statistically significant: local banks were less likely than non-local banks to cut relationships with their current customers during their financial crisis. The coefficient of $dlocal_{j2007}$ is negative and significant also after controlling for firms' and banks' characteristics, in column (2) and (3) respectively. Taken together, results from table 2 and 3 indicate that local banks kept funding their customers even if their hard-information indicators looked poorer – possibly because they made use of soft-information to identify good borrowers. Results from Table 3 confirm **Prediction 2:** when the quality of a firm worsened, as it was the

[19] We take the median of $local_{j2007}$ to identify whether a bank is local or not.

case in 2008, banks relying on soft information kept lending to their existing customers to a larger extent.

6. Robustness Checks

Our analysis so far has shown that firms borrowing from local banks in 2008 reported a lower rate of credit rationing than firms borrowing from not local banks. This result can be explained by the fact that local banks make a greater use of soft information compared with non-local banks. During periods of financial downturns, when hard-information deteriorates, local banks can use soft-information to validate their lending choices and keep their old customers.

Yet, there are potentially other explanations for our results: first, the lower credit rationing reported by firms predominantly funded by local banks could be driven by a heterogeneous impact the financial crisis had on the credit supply of local versus non-local banks. According to this view, local banks – who are indeed significantly more likely to be small than non-local banks – were subject to less strict capital regulatory requirements than not local banks during the financial crisis. It follows that local banks might have suffered from the liquidity contraction following the collapse of Lehman Brothers to a lower extent than non-local banks. This, in turn, might have translated into a higher funds availability for local banks, thus explaining why these lenders were less likely to tighten credit to their borrowers.

Second, local banks might have been less likely to turn down existing relationships during the financial crisis not because they were able to identify and keep funding good borrowers thanks to the use of soft information, but as a result of a "zombie-lending" strategy. Local banks might have lent to customers at risk of financial distress to "keep them alive". The reason for such behaviour is quite understandable: having limited diversification strategies – and also relative larger exposure towards the firms they fund – the losses local banks would incur in case of their customers' bankruptcy would be important, and might undermine the financial stability of the bank itself.

In what follows, we show than none of these competitive hypotheses find support in the data.

6.1. Intensive margin of credit

We first look at the intensive margin of credit to study whether there are any differences in the credit supply of local versus non-local banks that could justify our results. We estimate the following equation at the bank level:

$$\Delta\log\,(credit)_{jt} = \gamma_0 + \gamma_1 dlocal_{j2007} + \gamma_2 crisis_t + \gamma_3\big(dlocal_{j2007} * crisis_t\big) + \epsilon_{jt} \qquad (7)$$

where the dependent variable is the growth rate of credit of bank *j* in year *t*. This is constructed using data from the Credit Register.[20] $dlocal_{j2007}$ is a dummy that equals to one if bank *j*'s index of localism $local_{jt}$ is above the median value of the index in year 2007, and zero otherwise. We introduce the interaction term $dlocal_{j2007} * crisis_t$ and study whether, during the crisis, local banks lent to a greater extent than non-local banks.

Results from equation (7) are reported in Table 4 using OLS. We also include bank fixed effects in Column (2). As expected, the coefficient of the $crisis_t$ dummy reveals a dramatic slow-down in the credit growth at the bank level both in column (1) and (2). In addition, the coefficient of $dlocal_{j2007}$ is negative and significant in all specifications. Its sign and significance reveals that on average, the growth rate of credit from local banks is significantly lower than for non-local banks. However, the Diff-in-Diff coefficient, γ_3, is never significant. This suggests that during the financial crisis local banks did not lend more than non-local banks. Results from Table 4 rule out the hypothesis that our results are driven by differences in the credit supply between local and non-local banks resulting from different regulatory constraints. On the contrary, they corroborate our intuition that differences in lending are driven by a different type of relationships local versus non-local banks have with their customers.

[20] We use also Credit Registry data from 2006 to compute credit growth rate in 2007.

6.2. Zombie-lending strategies

To rule out that our results are driven by a zombie-lending strategy, we study the extensive margin of credit and look at the characteristics of the firms that local banks were more likely to keep funding during the financial crisis. We estimate the following regression equation at the loan level:

$$p(terminate)_{ij2008} = \gamma_0 + \gamma_1 dlocal_{j2007} + \gamma_2 firm\ characteristic_{i,2007} + \gamma_3 dlocal_{j2007} * firm\ characteristic_{i,2007} + \varepsilon_{ij} \quad (8)$$

where $p(terminate)_{ij2008}$ is the probability that a firm-bank relationship that was in place in year 2007 was terminated in 2008. $firm\ characteristic_{i,2007}$ is a set of firms' characteristics including ROA, revenues, size, leverage, and rating, evaluated before the financial crisis. We include the interaction term between $firm\ characteristic_{i,2007}$ and $dlocal_{j2007}$ to precisely assess which firms local banks were less likely to terminate existing relationships. Results from equation (8) are shown in Table 5. If our results were to be explained by a zombie-lending story, we should observe local banks to be less likely to terminate existing relationships with firms with worse balance sheet characteristics – that is, less profitable, smaller, riskier firms. This is however not the case – γ_3 is not significant when we look at the interaction term between $dlocal_{j2007}$ and firms' ROA or EBITDA, for instance. However, local banks appear less likely to cut existing relationships with high-leverage firms. Having high leverage does not imply that the firm is "bad", rather that it is using more resources possibly to invest in high-risk/high-return business activities. Still, being high leveraged may affect a firm's rating: this might explain why in column (5) we find local banks to be less likely to terminate existing relationships with firms with worse rating.

All in all, our results are consistent with a "soft-information" story – local banks kept funding opaque firms, which however do not appear to be less profitable or smaller firms. This corroborates **Prediction 2:** as the firms' hard-information quality worsened, only local banks kept lending, provided that soft information revealed that the firm's quality is good.

Finally, we also look at whether local banks were less likely to terminate existing relationships with firms with whom they had a relatively high credit exposure. It might be in fact the case that they kept funding these firms precisely because they wanted to be sure they could retrieve their outstanding credit. Column (7) of Table 5 however shows that the interaction term between $dlocal_{j2007}$ and $share\ credit\ bank_{i,2007}$ is positive and significant. This suggests that local banks, during the financial crisis, were less likely to interrupt relationships with firms they were less exposed to. Results from Table 5 lead us reject a zombie-lending story explaining our results, and once more confirm our hypothesis that local banks lent to a higher extent during the financial crisis precisely because they used soft information to a higher extent.

7. Conclusions

In this paper, we show that soft information can lead local lenders to grant credit, in cases when hard information would suggest the opposite.

We use data from the Italian credit market and we compare the behaviour of local versus non-local banks using a novel dataset that contains information on loans, as well as on firms' and banks' characteristics, before and after the Great Recession. Our identification strategy exploits the heterogeneity in banks' reliance on soft information to study the lending strategies of local versus non-local banks before and after the outburst of the Great Recession. It builds on the assumption that local banks use soft information to a higher extent than non-local banks but they rely on hard information to a similar extent.

Our results show that firms predominantly funded by local banks reported a lower credit rationing during the Great Recession. We also find that local banks were less likely to terminate existing relationships with their customers during the financial crisis, suggesting that local banks continued funding their clients even when borrowers' balance sheet variables worsened. Our results cannot be explained by demand effects, neither by a "zombie-lending" behaviour or by different impacts the financial crisis had on the credit supply of local versus local firms. This leads us to conclude that thanks to their greater reliance on soft information, local lenders supported their customers to a higher extent during bad times. Taken together, our findings suggest that thanks to relationship lending firms borrowing from local banks to a higher extent experienced more credit stability during the financial crisis, compared to firms borrowing from not local banks.

Our paper provides many interesting insights on the role of local banks. First, it highlights the importance of relationship lending, particularly in a period of financial downturn. Local banks, which rely more on soft information than not local banks, during the financial crisis played a more supportive role towards the firms they had already a lending history with.

Second, from a policy perspective, our results suggest that governments and central bankers should encourage the deepening in outreach of local financial intermediaries, as they prove to be important buffers against negative shocks for their customers.

Acknowledgements

The authors wish to thank, without implicating, Luigi Cannari, Piero Casadio, Riccardo De Bonis, Silvia Del Prete, Alessio D'Ignazio, Emilia Garcia-Appendini, Claire Lelarge, Massimo Omiccioli, Steven Ongena, Marcello Pagnini, Paola Rossi, David Scharfstein, Enrico Sette, Patrick Sevestre and seminar participants at the Università Politecnica delle Marche, at the XX International Tor Vergata Conference on Money, Banking and Finance, at Banque de France, Bank of Italy and University of Zurich for their useful comments and advices.

References

Agarwal, S., Hauswald, R., 2010. Distance and private information in lending. Review of Financial Studies 23, 2757–2788.

Albertazzi, U. and D.J. Marchetti (2010). "Credit supply, flight to quality and evergreening: an analysis of bank-firm relationships after Lehman."

Alessandrini P., Presbitero, A.F., Zazzaro, A., 2009. Banks, Distances and Financing Constraints for Firms. Review of Finance 13, 261-307.

Berger, A.N., Udell, G.F., 2002. Small Business Credit Availability and Relationship Lending: The Importance of Bank Organisational Structure. Economic Journal 477, 32-53.

Berger, A.N., Miller, H., Mitchell, 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, 237-269.

Bonaccorsi di Patti E., Sette, E., 2012. Bank balance sheets and the transmission of financial shocks to borrowers: evidence from the 2007-2008 crisis. Temi di discussione (Working Papers) 848, Banca d'Italia.

Casado-Díaz, J. M., 2000. Local labour market areas in Spain: a case study. Regional Studies 34, 843-856.

DeYoung, R., Hunter, W.C., Udell, G.F., 2004. Whither the Community Bank?. Journal of Financial Services Research 25, 81-84.

DeYoung, R., Frame, W.S., Glennon, D., Nigro P., 2011. The Information Revolution and Small Business Lending: The Missing Evidence. Journal of Financial Services Research 39, 19-33.

Farabullini, F. and Gobbi, G., 2000. Le banche nei sistemi locali di produzione, in: Signorini, L.F. (Eds.), *Lo sviluppo locale*, Donzelli, Rome.

Gambacorta, L., and Mistrulli, P.E., 2011. Bank heterogeneity and interest rate setting: What lessons have we learned since Lehman Brothers?. BIS Working Papers 359.

Garcia-Appendini, E. (2011) "Lending to small businesses: The value of soft information." *mimeo*

Gobbi, G., Sette, E., 2013. Do Firms Benefit from Concentrating their Borrowing? Evidence from the Great Recession. Review of Finance 18, 527-560.

Hannan, T.H., 2006. Retail deposit fees and multimarket banking. Journal of Banking & Finance 30, 2561-2578.

Hannan, T.H, and Prager, R.A., 2004. The competitive implications of multimarket bank branching. Journal of Banking & Finance 28, 1889-1914.

Jiménez, G., Salas, V., and Saurina, J., 2009. Organizational distance and use of collateral for business loans. Journal of Banking & Finance 33, 234-243.

Kremp, E., Sevestre, P., 2013. Did the crisis induce credit rationing for French SMEs?. Journal of Banking & Finance, 37, 3757-3772.

Liberti, J. M. (2003). "Initiative, Incentives and Soft Information: How does delegation impact the role of bank relationship managers?", *mimeo.*

Liberti, J. M. (2005). "How does organizational form matter? Distance, communication and soft information.", *mimeo.*

Liberti, J. M., and A. Mian (2009). "Estimating the effect of hierarchies on information use." *The Review of Financial Studies*, 22(10), 4057-4090.

Petersen, M., Rajan, R.G., 2002. Does distance still matter? The information revolution in small business lending. The Journal of Finance 57, 2533-2570.

Presbitero, A.F., Udell, G.F., Zazzaro, A., 2014. The Home Bias and the Credit Crunch: A Regional Perspective. Journal of Money, Credit and Banking 46, 53-85

Stein, J.C., 2005. Information production and capital allocation: Decentralized vs. hierarchical firms. The Journal of Finance 57, 1891-1921.

Stiglitz, J.E. and Weiss, A., 1981. Credit rationing in markets with imperfect information. The American Economic Review, 71(3), pp.393-410.

Williams, R.A., 1991. Measuring submarket specialisation by firms. Economic Letters 36, 291-416.

Appendix

Table 1. Descriptive Statistics at baseline

	Variables	Definition	Source	median	mean	sd
Panel A						
	p(credrat)	=1 if the firm reports being rationed	INVIND	0	0.027	0.163
Firm variables	ROA	Firm's profit over total assets	CERVED	0.868	1.526	6.115
	rating	Risk assessment on a scale from 1 to 9, where 1: very low risk and 9 very high risk	CERVED	5	4.596	1.776
	leverage	Firm's debt to equity ratio	CERVED	56.0198	52.262	30.441
	age	Years since foundation	CERVED	37	41.772	20.468
	size	=1 if the firm has 50+ employees	INVIND	1	0.635	0.482
Panel B						
	local	Banks' index of localism	Credit Register	0.530	0.571	0.363
	size bank	Banks' size expressed as an index that goes from 1 (large banks) to 7 (very small banks)	Bank of Italy Annual Report	5	5.023	1.438
Bank variables	capital ratio	Share of loans to supervisory capital	Supervisory Report	0.061	0.101	0.114
	funding ratio	Share of loans to non-financial companies not financed on the retail market (expressed as 1 minus the share of loans to non-financial companies financed on the retail market)	Supervisory Report	-0.120	-0.040	0.427
Panel C						
	nbank	Firm's number of bank relationships	Credit Register	7	7.979	5.554
	Δ log(credit)	Growth of credit at bank level	Credit Register	0.272	0.288	0.909
Bank lending relationships variables	share bank	Share of credit bank *j* lends to firm *i*	Credit Register	0.0004	0.0177	0.0852
	p(terminate)	Probability to terminate an existing bank lending relationship in the following year	Credit Register	0	0.068	0.251

Table 2. Credit rationing, local versus non-local banks

This table reports estimates of the determinants of firms' credit rationing. Among regressors, we include our main variable of interest, *local bank*, computed as a weighted average at the firm level of banks' index of localism, the weights being the shares of credit borrowed by the firm from each funding bank; the crisis dummy, and their interaction term, *local bank*crisis*. The dependent variable *p(credrat)* is obtained by combining the outcomes of two separate questions from the Bank of Italy INVIND survey: the first asked whether further funding was needed; the second whether banks had turned down requests for credit. We classify firms reporting a positive answer to both questions as financially constrained. All columns show Probit estimates. Firms controls added in the specification shown in column (2) include: ROA, age, size (number of employees), leverage, risk assessment, and number of bank links. Banks controls in column (3) include: size; funding ratio; capital ratio. Robust standard errors in brackets. *** coefficient significant at 1 per cent; ** at 5 per cent; * at 10 per cent. Marginal effects displayed.

	(1)	(2)	(3)
Dep. Variable	p(credrat)	p(credrat)	p(credrat)
local bank	0.050	0.032	0.064
	(0.032)	(0.029)	(0.042)
crisis	0.061***	0.055***	0.054***
	(0.008)	(0.008)	(0.008)
local bank*crisis	-0.056*	-0.061*	-0.058*
	(0.033)	(0.032)	(0.031)
Firm Controls	No	Yes	Yes
Bank Controls	No	No	Yes
Observations	4,257	4,257	4,257
Number of firms	2,373	2,373	2,373

Table 3. Extensive margin of credit

This table reports estimates of the determinants that a lending relationship between firm *i* and bank *j* that was in place in 2007 was terminated in 2008. Among regressors, we include our main variable of interest, *dlocal*, which is a dummy that takes the value of one if the bank's index of localism is above the median and zero otherwise. *Share bank* is the relative share of credit lent by bank *j* to firm *i*. Firms controls added in the specification shown in column (2) include: ROA, age, size (number of employees), leverage, risk assessment, and number of bank links. Banks controls in column (3) include: size; funding ratio; capital ratio. Robust standard errors in brackets. *** coefficient significant at 1 per cent; ** at 5 per cent; * at 10 per cent. Marginal effects displayed.

Dep. Variable	p(terminate)	p(terminate)	p(terminate)
	(1)	(2)	(3)
dlocal	-0.066***	-0.064***	-0.064***
	(0.011)	(0.011)	(0.011)
share bank	-0.212***	-0.258***	-0.249***
	(0.081)	(0.092)	(0.091)
Firm Controls	No	Yes	Yes
Bank Controls	No	No	Yes
Observations	15,423	14,944	14,944
Number of firms	2,373	2,373	2,373

Table 4. Intensive margin of credit

This table reports OLS estimates of the determinants of banks' annual rate of credit growth and total (log of) credit, at the bank level. We include as regressors our main variable of interests, the dummy *dlocal*, which takes the value of one if the bank's index of localism is above the median and zero otherwise; the *crisis* dummy, which equals to one in 2008 and zero in 2007, and their interaction term. The dependent variable in column (1) and (2) is computed as the difference in log credit granted by bank *j* between year *t* and *t-1*. Robust standard errors in brackets. *** coefficient significant at 1 per cent; ** at 5 per cent; * at 10 per cent.

Dep. Variable	growth credit	growth credit
	(1)	(2)
dlocal	-0.201**	-0.471*
	(0.097)	(0.264)
crisis	-0.424***	-0.446***
	(0.102)	(0.135)
local*crisis	0.017	0.030
	(0.126)	(0.202)
Bank FE	No	Yes
Observations	673	673
Number of banks	348	348

Table 5. Extensive margin of credit –Firms' characteristics

This table reports estimates of the determinants that a lending relationship between firm *i* and bank *j* that was in place in 2007 was terminated in 2008. Among regressors, we include our main variable of interest, *dlocal*, which is a dummy that takes the value of one if the bank's index of localism is above the median and zero otherwise. We then include the interactions between *dlocal* and firms' balance sheet characteristics: ROA, leverage, age, EBITDA, rating and size. *Share bank* is the relative share of credit lent by bank *j* to firm *i*. Robust standard errors in brackets. *** coefficient significant at 1 per cent; ** at 5 per cent; * at 10 per cent. Marginal effects displayed.

Dep. Variable	terminate	terminate	terminate	terminate	terminate	terminate	terminate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
dlocal	-0.064***	-0.007	-0.038	-0.051***	0.004	-0.083***	-0.083***
	(0.011)	(0.034)	(0.032)	(0.016)	(0.049)	(0.017)	(0.010)
ROA	-0.002***						
	(0.001)						
dlocal*ROA	0.001						
	(0.003)						
leverage		0.001***					
		(0.000)					
dlocal*leverage		-0.001**					
		(0.001)					
age			-0.000*				
			(0.000)				
dlocal*age			-0.001				
			(0.001)				
EBITDA				0.0003			
				(0.0003)			
dlocal*EBITDA				-0.002			
				(0.002)			
rating					0.008***		
					(0.002		
dlocal*rating					-0.016*		
					(0.010)		
firm size						0.001	
						(0.006)	
dlocal*firm size						0.050	
						(0.042)	
share credit	-0.217***	-0.218***	-0.210***	-0.224***	-0.218***	-0.216***	-1.301***
	(0.080)	(0.083)	(0.081)	(0.080)	(0.083)	(0.081)	(0.249)
dlocal*share credit							1.282***
							(0.255)
Observations	15,423	15,423	15,423	15,423	15,423	15,423	15,423

Appendix B

Table B1. Balancing checks – firms' variables

This table reports results from balancing checks used to test differences across firms funded by local versus non-local banks. We include as dependent variables the probability a firm reports being credit rationed, firms' ROA, ROE, EBITDA, size (a dummy which takes the value of one if the firm has more than 50 employees), age, leverage and rating. *Local bank* is computed as the weighted average at the firm level of banks' index of localism, the weights being the shares of credit borrowed by the firm from each funding bank. OLS estimates are shown. Robust standard errors in brackets. *** coefficient significant at 1 per cent; ** at 5 per cent; * at 10 per cent.

Dep. Variable	p(credrat)	ROA	ROE	EBITDA	size	age	leverage	rating
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
local bank	0.031	-1.165	-30.569	0.437	-0.389***	-7.012**	33.870***	1.392***
	(0.026)	(0.963)	(45.75)	(1.695)	(0.079)	(2.971)	(6.157)	(0.303)
Observations	2,500	2,500	2,500	2,500	2,500	2,500	2,500	2,500

Table B2. Before and after the crisis - Firms' variables

This table reports results from estimates used to test differences across firms' balance sheet characteristics before and after the financial crisis. We include as dependent variables the probability a firm reports being credit rationed, firms' ROA, ROE, EBITDA, size (a dummy which takes the value of one if the firm has more than 50 employees), age, leverage and rating. *crisis* is a dummy that takes the value of one in 2008 and zero in 2007. OLS estimates are shown. Robust standard errors in brackets. *** coefficient significant at 1 per cent; ** at 5 per cent; * at 10 per cent.

Dep. Variable	p(credrat)	ROA	ROE	EBITDA	size	age	leverage	rating
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
crisis	0.054***	-1.054***	-15.186*	-1.653***	0.004	-0.021	-5.338***	0.095
	(0.007)	(0.181)	(8.836)	(0.191)	(0.004)	(0.136)	(1.359)	(0.084)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N. of firms	2,373	2,373	2,373	2,373	2,373	2,373	2,373	2,373
Observations	4,257	4,257	4,257	4,257	4,257	4,257	4,257	4,257

Appendix C

In this section, we provide examples of our measure of bank localism. Consider the case of a credit market characterized by two local credit markets (A and B) and four banks (Bank 1, 2, 3 and 4). Table C1 shows two different scenarios, where we are interested, in particular, to assess Bank 4's degree of localism.

Table C1. Examples of the index computation

Panel A		Market A	Market B	A+B	index
	Bank 1	10	100	110	0.00
	Bank 2	10	100	110	0.00
	Bank 3	10	100	110	0.00
	Bank 4	10	0	10	1.56
	Total credit	40	300	340	

Panel B		Market A	Market B	A+B	index
	Bank 1	10	100	110	0.00
	Bank 2	10	100	110	0.00
	Bank 3	10	100	110	0.00
	Bank 4	0	10	10	0.02
	Total credit	30	310	340	

In the first scenario (Table C1, Panel A), Bank 4 lends all its credit in Market A, which is small compared to Market B, and populated by banks that lend relatively small, but identical credit volumes. On the contrary, Bank 4 does not lend at all in Market B, which is larger, and where other banks operate on a much larger scale. Market A is very important for Bank 4 – all its credit is concentrated there – and the bank itself is relatively important for the local market (its market share is 25 per cent). Therefore, the index of localism takes a high value, as the bank can be considered local, for our purposes.

Conversely, consider the scenario depicted in Panel B, Table C1. In this case, Bank 4 lends all its credit in a much larger credit market, Market B, where other banks have a larger and deeper presence. On the contrary, it does not lend at all in a smaller credit market like Market A. In this case, while the market is still very important for the bank (all its credit is concentrated there), the importance of Bank 4 in Market B as shown in Panel B is largely undermined by the presence of its competitors, but also by the fact that the share of credit lent by Bank 4 over the total credit lent in Market B is marginal – its market share is less than 3 per cent). Also, Bank 4 is not involved at all in Market A, where it could have been much more important given the relatively low presence of Bank 1, 2, 3. In this case, according to our index, this bank will be classified as less local than in Panel A.

Banks' localism versus other banks' dimensions

Table C2 shows how banks in our sample are classified based on our index of localism, as well as their size and institutional category, respectively.[21] Interestingly, Panel A of Table C2 shows that almost 45% of minor and small banks in our sample are classified as not local. A potential explanation for this apparently contradictory result is that these banks operate in markets with high bank competition and therefore, despite they are small, they fail in becoming the main local lender for their firms. Conversely, one big bank out of four is classified as local, potentially because despite its size it concentrates its credit in few local credit markets where

Similarly, Panel B of Table C2 reports a cross-tabulation between our index and banks' institutional category. Not surprisingly, almost 80% of Italian cooperative banks are classified as local; on the

[21] The dimensional and institutional category information are provided by the Bank of Italy, Annual Report 2009. Bank classification based on size builds on banks' assets. In addition, as our index is expressed as a continuous variable, to ease banks' classification we now consider the median of its distribution and classify intermediaries whose index is above the median as local, and non-local otherwise.

contrary, only one-fourth of mutual banks fall under this definition. Similarly, about one-fifth of joint-stock companies (Italian "*Società per azioni*") are local, as well.

Table C2. Banks' classification (local *versus* other characteristics)

Panel A: Bank classification based on size and localism

	Major banks	Big banks	Medium-sized banks	Minor and small banks	Total
Non-local banks	6	8	27	132	173
Local banks	0	1	0	173	174
Total	6	9	27	305	346

Panel B: Bank classification based on type and localism

	Limited company banks	Mutual banks	Cooperative banks (BCC)	Total
Non-local banks	122	20	31	173
Local banks	28	7	139	174
Total	150	27	170	346