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The Effects of Screening and Monitoring on Credit Rationing of SMEs

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In this paper, we seek to empirically assess which determinants of the capability and incentives of banks to screen and monitor firms are significant in explaining credit rationing to Italian SMEs. After testing for the presence of non-random selection bias and the potential endogeneity of some determinants of interest, the probit model results we obtain suggest that the average banking size and the multiple banking relationship phenomenon are statistically significant factors affecting credit rationing, presumably through their impact on the aforementioned banks' capability and incentives. Other potential determinants of banks' incentives to monitor and screen, such as local banking competition and firm' capacity to collateralize, are never significant. However, when we split the sample according to the level of competition in credit markets, we find that the estimated marginal effects of all significant determinants of interest are larger in absolute value than those obtained when using the whole sample.

(J.E.L.: D45, D10, D20, G21).

1. Introduction

In a market with imperfect and asymmetric information, it is hard to identify *good borrowers*, and there may be adverse selection and adverse incentive effects. In these circumstances, it is important to screen borrowers to identify those who are more likely to repay. In addition, it is important to monitor the actions of the borrowers *ex post*, to ensure that they use the funds properly and avoid undue risks.

The starting point of this paper is that banks may differ in their capability and incentive to screen and monitor borrowers. First, there

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is an ample literature documenting that large banks are more able to screen borrowers than small banks. Besides, banks may differ in their incentives to screen and monitor borrowers. As an example, banks facing firms involved in multiple banking relationships may have lower incentives, as multiple relationships make the acquisition of information less profitable.

In the hypothetical case of perfect screening and monitoring, no firm should be rationed – and each borrower should pay the *right* price to get the loan. However, distinguishing good from bad risks may be impossible or too costly, and credit rationing may be the outcome. The aim of this paper is to study whether banks' capability and incentives to screen and monitor borrowers affect credit rationing to small and medium sized firms (SMEs), more likely to be affected by this phenomenon due to their higher opacity. It is reasonable to expect that, other things being equal, when screening and monitoring by the banks is greater so is the probability of gauging the risk of default for each borrower or loan. In turn, the latter reduces the likelihood of credit being rationed, as the bank can attach the appropriate interest rate to each loan. On the basis of this hypothesis, we investigate to what extent some determinants of banks' capability/incentives to screen and monitor in local banking markets affect credit rationing to Italian SMEs. To assess the relevance of this problem with respect to the Italian economy, it is worth highlighting that SMEs make up more than 80 per cent of all Italian manufacturing firms, and loans are almost their only external financial source.

The present work uses a unique database that gives direct measures of credit rationing on Italian SMEs, provided by Capitalia – one of the largest Italian banks. Although there are many papers addressing the determinants of rationing, the novel idea of ours is to evaluate to what extent credit rationing is related to the capabilities and incentives of the banks to screen and monitor borrowers.

The rest of the paper is organized as follows. Section 2 surveys the literature on the main determinants of banks' screening and monitoring. Section 3 describes the empirical strategy. Section 4 highlights the main results obtained from the econometric analysis and illustrates the robustness tests performed. Section 5 concludes.

2. Determinants of Banks' Capability/Incentives to Screen and Monitor

A well-known result in the literature is that, when there is imperfect and asymmetric information in the credit market, adverse selection and adverse incentive effects are likely to occur. In these cases, as Stiglitz and Weiss (1981) pointed out, the interest rate does not allow the lender to discriminate between different types of borrower, and it is important to

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screen and monitor borrowers to reduce the probability that firms fail to repay the loans (see also Stiglitz and Weiss, 1988).

Asymmetric information problems are more likely to occur when banks deal with small and medium sized enterprises, due to the high opacity of the latter (Berger *et al.*, 2001; Beck *et al.*, 2004). Regardless of the degree of asymmetric information, banks may differ in capabilities and incentives to screen and monitor borrowers. First, there is an ample literature documenting that a bank's size affects its lending technology (see – among others – Stein, 2002; Berger *et al.*, 2005). In evaluating borrowers and investment projects, large banks rely more heavily on hard information, i.e. information that is verifiably documented in a report that the loan officer passes on to his superiors: the company's income statements, balance sheet, credit rating and the like. It follows that large banks rely more on screening, and screened-based lending is likely to reduce credit rationing of big and more transparent firms. By contrast, small banks have a comparative advantage in the area of soft information, i.e. information that is typically gathered by personal contact (Berger and Udell, 2006).[1] Thus, large banks have a relative advantage in screening techniques, but small ones may use relationship lending to get accurate information on borrowers, and the prediction on the effects of bank size on credit rationing to SMEs is not clear-cut.[2]

Apart from the lending technology, banks' ability to efficiently screen and monitor borrowers is related to the possibility of perfectly diversifying their portfolios (Diamond, 1984). When this is not feasible, screening and monitoring depend on their equity capital: the greater the latter, the greater banks' screening and monitoring and the lower the credit rationing. In relation to this latter, Chiesa (1998) proves that a concentrated banking industry, one where bank capital is held by few banks, leads credit allocation to be closer to the social optimum.

As far as the incentives to screen and monitor are concerned, the degree of competition in the credit market may affect banks' propensity to generate information on loan applicants. The traditional view of market power highlights the beneficial effects of banking competition on the cost and the availability of credit (Beck *et al.* 2004; de Mello, 2004). On the other hand, Gehrig (1998) and Hauswald and Marquez (2006) show that as competition in local markets increases, investment in information acquisition falls, because it is less profitable. Thus, as competition heightens, loans' average quality may deteriorate and credit rationing may

[1] Information and Communication Technology (ICT) has increased the capacity for collecting hard information on borrowers, but not soft information. Actually, the new technologies have also shifted the emphasis from strict *ex ante* screening and costly *ex post* monitoring to frequent *ex post* monitoring and prompt intervention (Petersen and Rajan, 2002).

[2] Sapienza (2002), among others, has shown that when banks become larger they reduce the supply of loans to small firms.

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increase.[3] In relation to this point, a number of works (Petersen and Rajan, 1995; Dell'Ariccia *et al.*, 1999; Boot and Thakor, 2000) have noted that with asymmetric information between lenders and borrowers, the relationship between market power and credit availability may not be negative, because banks with market power are better able to build lending relationships with borrowers. From this discussion it follows that, although competition in the credit market may have beneficial effects on credit supply, intense competition may weaken the incentive to screen and monitor borrowers, with detrimental effects on credit to SMEs.[4]

Another potential factor affecting banks' incentives to screen and monitor is the phenomenon of multiple banking relationships. As claimed by Thakor (1996) and Carletti (2004), multiple banking relationships may reduce the incentive to screen or monitor, because each bank bears the full cost but must share the benefits with the other lenders. That is, free-riding may be a problem, resulting in a higher probability of rationing. Accordingly, we expect that the higher the number of banks lending to a single firm, the lower each one's incentive to screen and monitor, and the greater the credit rationing.[5]

Finally, banks may use credit contracts to screen loan applicants. Although Stiglitz and Weiss (1981) pointed out that in a market with imperfect information the lender is not able to discriminate between different types of borrower, Bester (1985) showed that banks can offer a menu of contracts, with a range of both collateral requirements and the rate of interest, to discriminate among borrowers. Those with lower probability of default should be more willing to accept higher collateral requirements in exchange for a given reduction in the rate of interest. Thus, collateral requirements can serve as a self-selection mechanism and eliminate credit rationing. But, collateral may have a countervailing effect on the incentive of the banks to screen and monitor borrowers. Safeguarded by collateralized debt, the bank may lack incentive to screen and monitor projects and applicants, and too many bad projects could be funded, and too many able entrepreneurs could fail (Manove *et al.*, 2001). This in turn is likely to increase credit rationing.

[3] In this situation, merging for informational reasons may increase the incentive to screen borrowers, and transparent firms are less likely to be rationed (Chiesa, 1998).

[4] Recently, Guiso *et al.* (2006) have found that more competition in the Italian credit market reduces borrowers' probability of being credit rationed. However, their model does not consider informational problems in different markets and, most important, their dataset does not contain the really small firms, which are the most likely to be rationed. Their result is, however, consistent with the fact that large firms are more transparent and less likely to be rationed.

[5] However, Detragiache *et al.* (2000), among others, stated that having multiple banking relationships is beneficial to firms, in that it increases the probability of receiving credit and lowers the interest rate. Carletti *et al.* (2007) show that when the agency problem between banks and depositors is sufficiently severe, the benefit of greater diversification dominates the drawbacks of free-riding and duplication of effort, and multi-lending leads to more per-project monitoring than one-bank lending.

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The literature so far surveyed suggests that there may be several determinants that – by affecting the screening and monitoring capability/incentives of banks – might have influence on firms' credit rationing. In what follows, our aim is to verify the statistically significant determinants for the case of Italian SMEs.

3. Empirical Strategy

3.1. The Econometric Specification

Because credit rationing is a discrete phenomenon, we take a limited dependent variable approach. More precisely, we adopt the following probit model:

$$
\begin{aligned}
&Rat_{it} = 1 \quad \text{if } r^* = \beta_0 + X'_{it}\beta_1 + Z'_{it}\beta_2 + \sum_t \delta_t T_t + \eta_{it} > 0; \\
&Rat_{it} = 0 \quad \text{otherwise,}
\end{aligned}
\tag{1}
$$

where RAT is our proxy of credit rationing, a dummy variable coded 1 if a firm – in a period – was credit-rationed and 0 otherwise, r^* is a latent variable representing the disutility of being credit-constrained, the subscripts i and t refer to firms and time, respectively, the vector X includes the observable determinants of capability and incentives to screen and monitor described below, the vector Z is comprised of the control variables illustrated in what follows, T_t is a comprehensive set of time fixed effects, and the error term η capturing unobservable determinants of credit rationing is assumed to be *i.i.d N(0, 1).*

We expect that credit rationing depends on the capability and incentives that banks have to screen and monitor firms. In turn, these skills and incentives are determined by several factors, which are summarized in Table 1:

As far as the main capability determinants are concerned, we employ the average total assets (TAB) and the average capital (KB) of the banks

Table 1: Determinants of Banks Capability and Incentives to Screen and Monitor, and Their Impact on Credit Rationing

Capability	
Banks' size	–
Incentives	
Banking competition	+/–
Multiple banking relationships	+
Firm collateral	+/–

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within a province[6] as proxies for the size of the local banking market.[7] As concerns the first determinant of banks' incentives, we employ an index of local banking competition (LBCpca). It is obtained by Principal Component Analysis (PCA) of two indicators of competition at provincial level, the Panzar and Rosse (1987) *H-statistic* and the complement to one of the traditional Hirschman-Herfindahl index.[8] The multiple banking relationship phenomenon is proxied by the number of banks lending to a firm (NBAN) and the credit share that a firm obtained by its main bank (MAIN). Further, the ratio of tangible assets on total assets (COLL) is used as a measure of a firm's capacity to collateralize. Finally, we add to our model a vector ($\underline{\mathbf{Z}}$) of control variables, both at firm and credit market level. The former comprises: firm's total assets (TA), firm's age (AGE) and its square (AGE2), a measure of firm's riskness (RISK), firm's amount of bank debt on total assets (BDEBT), an indicator of firm's profitability (ROA), the ratio of firm's liquidity on total assets (LIQUI), Pavitt dummies (PAV) and a dummy for group membership (GRU). As control variables at provincial level we take account of: real gross domestic product (GDP), population (POP), the amount of deposits (DEP), credit market riskness (proxied by the ratio of bad loans on total lending, BADL), the underground economy (measured as the number of irregular workers over population, UNDERG), the legal enforcement in the area (measured by the number of backlog civil trials, first degree of judgement, on population – ENFO).

We expect that the greater a firm's total assets and age, the lower the probability of being rationed. Moreover, by means of its square term, we allow age's impact to have a switching point. Higher firm's risk and debt ratio should increase monitoring and rationing. Opposite effects are expected for the performance indicators, namely return on assets and liquidity. The probability of being rationed should be negatively affected also by the membership to a group, whereas it should be higher for firms operating in the riskier sectors (PAV3 and PAV4). Real GDP controls for the effects of the business cycle at provincial level, whereas POP and DEP

[6] We conduct our empirical analysis at provincial level, because 'from an economic point of view the natural unit of analysis is the province' (Guiso *et al*., 2004).

[7] We regret that we lack information on the individual size of the banks in relationship with each firm of our sample, thus we employ the above-mentioned aggregated measures.

[8] We compute these indicators as illustrated in Appendix A. The principal components method, which serves to minimize the arbitrariness of aggregation, allows one to describe a set of variables by means of a new smaller set of lower dimensionality and is accordingly used to deal with the problem of multi-collinearity that might result from the presence of a group of highly correlated regressors. The new variable is a linear combination of the original set, with weights chosen to maximize the variance explained by the composite variable. In our case, we want to summarize some measures of local banking competition by means of two (separate) numbers that best capture their cumulative effects. Note that prior to the PCA, we standardized the variables in order to prevent the variable with the highest variance from dominating the resulting index. Finally, note that (1-HHI) gives a measure that is homogeneous to the *H-statistic*, with the consequence that the resulting index behaves like the Panzar and Rosse indicator: higher values mean more competition.

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are introduced to take into account the size of the local credit market. Finally, credit rationing is expected to be heightened where the credit market riskness and the diffusion of the irregular economy are higher, and the legal enforcement is weaker.

3.2. *The Econometric Method*

The estimation of model 1 poses two problems. First, the crucial hypothesis (random distribution of credit-constrained and non-credit constrained agents) on which the probit model is based could be violated. In fact, we only observe the discrete phenomenon for the agents who actually applied for a loan. If the latter are systematically different from those who did not apply, selection bias may arise. Besides, two main coefficients of interest (NBAN and LBCpca) may suffer from a simultaneous causality bias. For instance, it could be that firms that find themselves credit-rationed develop multiple banking relationships in an attempt to obtain more credit.

So that, to control for (and test the significance of) the potential correlation between demand and credit rationing a Heckman probit is employed.[9] To mitigate the potential endogeneity aforementioned, the variables under question are lagged.[10] When doing so – according to estimates not reported, but available upon request – the selection test (a likelihood ratio test of independent equations) is not significant. Thus, the two processes (demand for credit and credit rationing) may be estimated separately, and we can focus on model (1). In order to account for the endogeneity of banking relationship and local competition, we adopt an instrumental variable probit model where the instruments are: an index of criminality (given by the ratio of violent crimes on population), an indicator of infrastructural endowment, and two ratios indicating the density and dispersion of population; the former is measured as the ratio of population to surface (in square kilometres), and the latter by the ratio of population to the number

[9] We have specified the demand for credit by means of a probit model where the latent variable is explained by the same explanatory variables of the vector X, with the addition of two instruments: the dummy for the southern regions and a productivity measure (given by labour cost on value added). These variables are expected to affect only the selection process, and their exclusion from the substantial equation – identifying the model – is justified also from a statistical point of view (none of them is significant when included in the main equation). Under the assumption that the error terms of the two probits are jointly normal, they may be jointly estimated by using the maximum likelihood method. Notice that our database lacks information on the demand for loans, so we construct the dependent variable of the selection process by combining information drawn from the credit rationing question in the Capitalia's surveys with information from the firm's accounts. More precisely, when a firm does not respond to that question, we consider a positive annual change in bank debt as an indicator of a demand for credit.

[10] We have also investigated the possibility of estimating an instrumental Heckman probit. Unfortunately, as Wooldridge (2002, p. 571) summarizes, allowing for endogenous explanatory variables in such models 'is difficult, and it could be the focus of future research'.

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of municipalities.[11] All these variables are measured at the province level and pass (a version of) the *Sargan test* of over-identifying restrictions. According to a Wald test of exogeneity (Wooldridge, 2002), though, we cannot reject the hypothesis that the two variables under scrutiny are exogenous. Therefore, we estimate a pooled probit model. Table 5 reports the latter estimates along with the outcomes of the aforementioned.

3.3. The Data

All the variables at firm level are drawn from the 7th, 8th and 9th Capitalia's surveys on Italian manufacturing firms, with the exception of RISK, which Moody's KMV has computed for us on Capitalia's balance-sheet data.[12] Because data on firms span from 1995 to 2003 but information on credit rationing is available only for the last year of each survey (1997, 2000, 2003), we refer our analysis only to these years. On the other hand, we compute the variables TAB, KB and LBCpca on Italian Banking Association (ABI) data, as described in Appendix A. DEP and BADL are drawn from the Bank of Italy dataset, whereas the rest of the variables at provincial level come from the Italian National Statistical Institute (ISTAT).

All the variables included in expression (1) are described in Table 2, whereas Table 3 reports their summary statistics. It is worth mentioning that, to account for the presence of potential outliers, before estimating our model, we drop all observations lying in the first and last 0.5 per cent of each variable distribution.

4. Results and Robustness Checks

Our estimation results are reported in Tables 5 and 6. Column 2 of Table 5 shows that, among our variables of interest, only the estimated coefficients of NBAN, MAIN and KB are statistically significant, whereas those of TAB, LBCpca and COLL are not. As expected, a higher number of banks with which a firm has relationships (NBAN) seems to increase the

[11] The information needed to compute these variables come from ISTAT, with the exception of that concerning the provincial infrastructural endowment, which has been drawn from the Tagliacarne Institute dataset.

[12] These surveys were conduct on a representative sample of Italian manufacturing firms. The 7th survey (1998) reports data for a panel of 4493 firms for the period 1995–1997; the 8th (2001) has data on a panel of 4680 firms for 1998–2000; the 9th (2004) on 4289 firms for the period 2001–2003. These surveys provide such qualitative data as sector, group membership, ownership, financial structure and access to the credit market. Capitalia also provides balance-sheet data on the firms surveyed. By matching qualitative and accounting data, we obtain an unbalanced panel of 5998 firms in the period 1995–2003, for a total of 25,530 observations. Although the dataset includes firms up to 500 employees, we only consider SMEs (up to 250 employees).

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Table 2: Description of Variables Used in the Estimation

Variable	Description
RAT_{it}	Dummy = 1 if firm *i* asked more credit without receiving it, and zero otherwise
$NBAN_{it}$	Number of banks from whom firms borrow
$MAIN_{it}$	Percentage of credit that firm *i* obtained from the main bank
$COLL_{it}$	Tangible assets to bank debt
TAB_{pt}	Banks' total assets
KB_{pt}	Banks' equity
$LBCpca_{pt}$	Measure of local banking competition built by Principal Component Analysis on (the complement to one of) HHI and on H statistic
TA_{it}	Total assets of the firm
AGE_{it}	Current year minus firm's year of establishment
$RISK_{it}$	One-year *ex ante* probability of default provided by RiskCalc(tm) Italy, developed by Moody's KMV
$BDEBT_{it}$	Bank debt to total assets
ROA_{it}	Firms gross profits to firms total assets
$LIQUI_{it}$	Cash, accounts receivable, other current assets to TA
GRU_{it}	Dummy = 1 if firm belongs to a group, and zero otherwise
$PAV1_{it}$	Dummy = 1 if firms belong to the traditional sectors, and zero otherwise
$PAV2_{it}$	Dummy = 1 if firms belong to the scale sectors, and zero otherwise
$PAV3_{it}$	Dummy = 1 if firms belong to the specialized supplier sectors, and zero otherwise
$PAV4_{it}$	Dummy = 1 if firms belong to the science based sectors, and zero otherwise
GDP_{pt}	Gross domestic product
POP_{pt}	Population
DEP_{pt}	Total deposits in the local market
$BADL_{pt}$	Bad loans to total loans
$UNDERG_{pt}$	Irregular number of labour units
$ENFO_{pt}$	Backlog of civil trials pending (first degree of judgement) to population
$SOUTH_{i}$	Dummy = 1 if firms belong to the Italian Southern regions, and zero otherwise

Notes: Indexes *i, p* and *t* indicate firm, province and time, respectively (see note to Table 3). Variables at firm level are drawn for the 7th, 8th and 9th Capitalia surveys (*Indagini sulle Imprese Manufatturiere*), with the exception of RISK. Variables LBCpca, TAB and KB are computed as described in Appendix A. Variables DEP and BADL are from Bank of Italy, whereas the rest of the variables at provincial level are drawn from ISTAT.

probability of being constrained. Further, the percentage of lending with the main bank (MAIN) tends to increase the latter probability, even though the estimated coefficient is only marginally significant. Moreover, in line with our expectations, the probability of being credit-rationed seems to be lower the higher the average bank size (KB) in local markets. Finally, the results do not indicate a significant impact of local banking competition (LBCpca) and firms' capacity to collateralize (COLL) on credit rationing. As far as the control variables are concerned, only those capturing firms' characteristics are significant and display the expected sign.[13] Indeed, larger firm size has a negative effect on the probability of being credit-rationed. A similar result is found for AGE: an older firm seems to be less rationed, even though this negative effect turns into positive for the oldest sample

[13] Among the remaining control variables, only the GDP indicator is marginally significant.

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Table 3: Summary Statistics

	Mean	Std. Dev.	Min	Max	Median
RAT	0.080	0.271	0	1	0
NBAN*	5	3	1	20	5
MAIN**	34.707	25.016	0	100	30
COLL**	23.051	15.340	0.438	72.084	20.731
TAB#	24,893	43,744	631	189,540	9709
KB#	1421	2339	19	10,639	676
LBCpca	−0.058	0.695	−1.192	6.005	−0.199
TA§	4578	5411	275	42,481	2589
AGE*	24	15	1	96	21
RISK**	0.294	0.338	0.060	2.910	0.190
BDEBT**	21.640	19.769	0	70.988	19.487
ROA**	4.028	6.506	−19.665	38.859	2.652
LIQUI**	55.499	23.246	1.520	95.584	59.007
GRU	0.192	0.394	0	1	0
PAV1	0.525	0.499	0	1	1
PAV2	0.182	0.386	0	1	0
PAV3	0.257	0.437	0	1	0
PAV4	0.036	0.187	0	1	0
GDP#	24,484	30,895	1236	120,721	13,203
POP*	1,018,736	1,046,482	89,955	3,775,765	651,996
DEP#	7230	11,517	194	45,500	3123
BAD**	5.593	4.763	1.442	32.520	3.988
UNDERG*	54,855	61,820	5046	299,302	33,005
ENFO**	3.564	2.793	1.013	16.110	2.532
SOUTH	0.145	0.352	0	1	0

*In units; **In percentage. §In thousands of euro. #In million of euro. The other variables are dummies. For the description of the variables, see Table 2. The number of firms in the sample is 4005, except for RAT (2578), GRU (4000) and Pavitt dummies (3988). The sample's firms is representative of 102 provinces (on a total of 103 existing in Italy in the years which the econometric analysis refers to, that is 1997, 2000 and 2003. The missing province is Enna). The total number of observations is 5183 (620 for 1997, 2280 for 2000 and 2283 for 2003), except for RAT (609 for 1997, 2202 for 2000 and 300 for 2003, summing to 3111), GRU (620 for 1997, 2277 for 2000 and 2277 for 2003, summing to 5174) and Pavitt dummies (620 for 1997, 2280 for 2000 and 2265 for 2003, summing to 5165).

firms. More risky and indebted firms display a higher probability of being rationed, whereas better performance indicators (profitability and liquidity) seem to lower this probability.[14]

To test the robustness of our findings, we carry out extensive sensitivity checks. We first look at the correlation matrix among the regressors we employ (see Table 4), and re-estimate model (1) by dropping

[14] As the notes of Tables 5 and 6 spell out, some explanatory variables (TAB, KB, TA, BDEBT, ROA, LIQUI, DEP and BADL) are lagged once, in order to mitigate potential simultaneity biases. While the dependent variable (RAT) is available only for the 3 years 1997, 2000 and 2003 (the last year of each Capitalia survey we consider), all the mentioned explanatory variables are available on a yearly basis along the period 1995–2003; therefore, the lagged values refer to the years preceding those considered in the analysis (hence to 1996, 1999, and 2002). Only in Subsection 3.2, when lagging the variables suspected of endogeneity (NBAN and LBCpca), because one of them (NBAN) is available only for 1997, 2000 and 2003, the lag of an observation is the previous survey value (so that, for instance, the lag of a 2000's observation is the 1997 value).

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Table 4: Correlation Matrix

	NBAN	MAIN	COLL	TAB	KB	LBCpca	TA	AGE	RISK	BDEBT	ROA	LIQUI	GRU	PAV1	PAV2	PAV3	PAV4	POP	GDP	DEP	BADL	UNDERG	ENFO
NBAN	1.000																						
MAIN	–0.282	1.000																					
COLL	–0.071	0.069	1.000																				
TAB	–0.026	–0.021	–0.061	1.000																			
KB	–0.022	–0.026	–0.065	0.995	1.000																		
LBCpca	–0.052	0.035	0.103	–0.341	–0.342	1.000																	
TA	0.409	–0.127	0.031	0.050	0.059	–0.019	1.000																
AGE	0.110	–0.018	0.049	0.120	0.125	–0.024	0.182	1.000															
RISK	–0.009	0.054	–0.049	0.020	0.017	0.018	–0.103	–0.114	1.000														
BDEBT	0.383	–0.037	0.070	–0.063	–0.061	0.008	0.281	0.077	0.120	1.000													
ROA	–0.106	–0.041	–0.148	0.055	0.057	–0.048	–0.024	–0.017	–0.450	–0.281	1.000												
LIQUI	0.209	–0.113	–0.486	0.010	0.015	–0.074	0.169	0.125	–0.103	0.377	0.040	1.000											
GRU	0.130	–0.050	–0.020	0.043	0.048	–0.032	0.325	–0.031	–0.030	0.078	0.006	0.039	1.000										
PAV1	–0.021	0.055	0.085	–0.158	–0.158	0.060	–0.029	0.011	0.024	0.097	–0.113	0.012	–0.070	1.000									
PAV2	–0.009	–0.023	0.061	0.054	0.053	–0.005	0.018	–0.012	–0.012	–0.029	0.022	–0.072	0.026	–0.496	1.000								
PAV3	0.032	–0.036	–0.135	0.104	0.107	–0.063	0.014	0.006	–0.029	–0.079	0.089	0.060	0.043	–0.618	–0.278	1.000							
PAV4	0.001	–0.015	–0.037	0.068	0.062	–0.003	0.007	–0.017	0.027	–0.016	0.048	–0.025	0.030	–0.203	–0.091	–0.114	1.000						
POP	–0.053	–0.002	–0.048	0.894	0.879	–0.342	0.031	0.094	0.034	–0.062	0.025	0.001	0.020	–0.155	0.073	0.078	0.081	1.000					
GDP	–0.035	–0.015	–0.069	0.971	0.960	–0.367	0.041	0.116	0.025	–0.064	0.054	0.012	0.034	–0.173	0.067	0.104	0.081	0.960	1.000				
DEP	–0.031	–0.018	–0.063	0.988	0.977	–0.360	0.042	0.115	0.023	–0.063	0.054	0.010	0.035	–0.165	0.064	0.099	0.079	0.935	0.992	1.000			
BADL	–0.082	0.037	0.185	–0.246	–0.268	0.292	–0.018	–0.090	0.048	0.007	–0.106	–0.098	–0.040	0.090	0.030	–0.131	0.003	–0.135	–0.255	–0.238	1.000		
UNDERG	–0.070	0.017	–0.029	0.768	0.739	–0.326	0.000	0.052	0.047	–0.060	0.006	–0.018	–0.005	–0.128	0.076	0.039	0.094	0.958	0.868	0.838	–0.016	1.000	
ENFO	–0.067	0.043	0.142	–0.163	–0.185	0.086	0.002	–0.119	0.037	0.008	–0.106	–0.071	–0.013	0.119	0.001	–0.141	0.009	0.062	–0.131	–0.135	0.645	0.228	1.000

Note: For the description of the variables, see Table 2.

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Table 5: Estimation Results

	Dependent variable: RAT					
	(2) ***General model: equation (1)***	*(3)* ***Dropping variables TAB, POP, DEP, UNDERG from the general model***	*(4)* ***Parsimonious model*** (general simple outcome from model in column 3)	*(5)* ***Parsimonious with clustering at the province level***	*(6)* ***Parsimonious model with clustering at the firm level***	*(7)* ***Parsimonious model with bootstrapped SEs (1000 replications)***
NBAN	0.059***	0.058***	0.060*** (.0056)	0.060***	0.060***	0.060***
	[0.016]	*[0.016]*	*[0.016]*	*[0.018]*	*[0.016]*	*[0.016]*
MAIN	0.003*	0.003*	0.003* (.0003)	0.003*	0.003*	0.003*
	[0.002]	*[0.002]*	*[0.002]*	*[0.002]*	*[0.002]*	*[0.002]*
COLL	−0.002	−0.003				
	[0.003]	*[0.003]*				
TAB	0.800					
	[0.662]					
KB	−0.422**	−0.456***	−0.391*** −(.0363)	−0.391**	−0.391***	−0.391***
	[0.209]	*[0.153]*	*[0.145]*	*[0.160]*	*[0.146]*	*[0.150]*
LBCpca	−0.104	−0.104				
	[0.073]	*[0.067]*				
TA	−0.111*	−0.109*	−0.121** −(.0112)	−0.121***	−0.121**	−0.121**
	[0.057]	*[0.057]*	*[0.054]*	*[0.044]*	*[0.051]*	*[0.052]*
AGE	−0.018**	−0.018**	−0.018** −(.0017)	−0.018**	−0.018**	−0.018**
	[0.008]	*[0.007]*	*[0.007]*	*[0.007]*	*[0.008]*	*[0.008]*

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AGE2	.0003***	.0003***	.0003***	(.00002)	.0003***	.0003***	.0003***
	[0.0001]	*[0.0001]*	*[0.0001]*		*[0.0001]*	*[0.0001]*	*[0.0001]*
RISK	0.301***	0.312***	0.317***	(.0294)	0.317***	0.317***	0.317***
	[0.098]	*[0.097]*	*[0.095]*		*[0.078]*	*[0.100]*	*[0.103]*
BDEBT	0.008***	0.008***	0.008***	(.0007)	0.008***	0.008***	0.008***
	[0.003]	*[0.003]*	*[0.002]*		*[0.002]*	*[0.003]*	*[0.002]*
ROA	−0.032***	−0.032***	−0.032***	−(.0030)	−0.032***	−0.032***	−0.032***
	[0.008]	*[0.008]*	*[0.008]*		*[0.007]*	*[0.008]*	*[0.008]*
LIQUI	−0.006***	−0.006***	−0.005**	−(.0004)	−0.005**	−0.005**	−0.005**
	[0.002]	*[0.002]*	*[0.002]*		*[0.002]*	*[0.002]*	*[0.002]*
GRU	0.027	0.027					
	[0.110]	*[0.110]*					
PAV2	−0.040	−0.038					
	[0.112]	*[0.111]*					
PAV3	0.127	0.130	0.154*	(.0153)	0.154	0.154	0.154
	[0.098]	*[0.097]*	*[0.092]*		*[0.095]*	*[0.094]*	*[0.096]*
PAV4	−0.180	−0.164					
	[0.211]	*[0.210]*					
GDP	0.872*	0.597***	0.553***	(.0513)	0.553***	0.553***	0.553***
	[0.507]	*[0.167]*	*[0.160]*		*[0.182]*	*[0.162]*	*[0.164]*
POP	0.452						
	[0.533]						
DEP	−1.282						
	[0.817]						

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Table 5: Continued

	Dependent variable: RAT					
	(2) ***General model: equation (1)***	*(3)* ***Dropping variables TAB, POP, DEP, UNDERG from the general model***	*(4)* ***Parsimonious model*** (general simple outcome from model in column 3)	*(5)* ***Parsimonious with clustering at the province level***	*(6)* ***Parsimonious model with clustering at the firm level***	*(7)* ***Parsimonious model with bootstrapped SEs (1000 replications)***
BADL	0.017	0.021**	0.017** (.0016)	0.017**	0.017**	0.017**
	[0.013]	*[0.009]*	*[0.008]*	*[0.009]*	*[0.007]*	*[0.007]*
UNDERG	−0.337					
	[0.298]					
ENFO	−0.006	−0.013				
	[0.024]	*[0.017]*				
Wald test (a)	379.8	377.1	373.1	402.9	323.25	311.28
(df)	25	21	15	15	15	15
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Wald test (b)	0.810	0.960				
p-value	*0.6654*	*0.6184*				
Test of over-identifying	2.427	0.755				
restrictions:	*0.2972*	*0.686*				
Pseudo R2	0.229	0.228	0.225	0.225	0.225	0.225
Log pseudolikel.	−638.2	−639.6	−641.9	−641.9	−641.9	−641.9
Observations	2990	2990	2993	2993	2993	2993

Note: For the description of the variables, see Table 2. In square brackets are reported the standard errors, which are robust in columns 5–7. Marginal effects are reported in round brackets. Constant and time dummies included but not reported. Wald statistic (a) tests the null hyphotesis that all the coefficients are jointly zero. Wald statistic (b) tests the null hyphotesis that NBAN and LBCpca are exogeneous. The reported over-identifying restrictions test is a version of the Sargan test for IV probit models. The variables TAB, KB, TA, BDEBT, ROA, LIQUI, DEP and BADL are lagged once. Besides, TAB, KB, TA, POP, GDP, DEP and UNDERG are in natural logarithms.

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Table 6: Robustness

	Dependent variable: RAT									
	(2) **Benchmark model for the values of dummy PAV4 = 0**		*(3)* **Benchmark model for the values of LBCpca > medianLBCpca**		*(4)* **Benchmark model for the values of LBCpca ≤ medianLBCpca**		*(5)* **Benchmark model for the values of dummy South = 0**		*(6)* **Benchmark model for the values of dummy South = 1**	
NBAN	0.061***	(.0104)	0.101***	(.0141)	0.026	(.0047)	0.056***	(.0101)	0.092**	(.0112)
	[0.016]		*[0.024]*		*[0.022]*		*[0.018]*		*[0.045]*	
MAIN	0.004*	(.0006)	0.007**	(.0010)	0.0002	(.00004)	0.003	(.0005)	0.006	(.0007)
	[0.002]		*[0.003]*		*[0.003]*		*[0.002]*		*[0.004]*	
COLL										
TAB										
KB	−0.313**	−(.0533)	−0.613***	−(.0860)	−0.098	−(.0176)	−0.361*	−(.0655)	−0.196	−(.0239)
	[0.152]		*[0.183]*		*[0.334]*		*[0.193]*		*[0.349]*	
LBCpca										
TA	−0.115**	−(.0196)	−0.172**	−(.0241)	−0.068	−(.0121)	−0.112*	−(.0203)	−0.140	−(.0171)
	[0.054]		*[0.081]*		*[0.070]*		*[0.057]*		*[0.128]*	
AGE	−0.020**	−(.0034)	−0.025**	−(.0034)	−0.014	−(.0025)	−0.018*	−(.0032)	−0.011	−(.0013)
	[0.008]		*[0.012]*		*[0.014]*		*[0.009]*		*[0.028]*	
AGE2	0.0003**	(.00005)	0.0004**	(.00006)	0.0002	(.00003)	0.0003**	(.00005)	−0.0003	(.00000)
	[0.0001]		*[0.0002]*		*[0.0002]*		*[0.0001]*		*[0.0005]*	
RISK	0.342***	(.0583)	0.317**	(.0445)	0.301**	(.0539)	0.316***	(.0572)	0.223	(.0271)
	[0.102]		*[0.151]*		*[0.149]*		*[0.113]*		*[0.284]*	
BDEBT	0.007***	(.0013)	0.006	(.0009)	0.008**	(.0015)	0.007**	(.0012)	0.013*	(.0015)
	[0.003]		*[0.004]*		*[0.003]*		*[0.003]*		*[0.007]*	
ROA	−0.032***	−(.0055)	−0.018	−(.0025)	−0.050***	−(.0089)	−0.030***	−(.0055)	−0.052**	−(.0063)
	[0.009]		*[0.012]*		*[0.013]*		*[0.009]*		*[0.022]*	
LIQUI	−0.005**	−(.0008)	−0.002	−(.0003)	−0.006**	−(.0012)	−0.004*	−(.0007)	−0.008	−(.0010)
	[0.002]		*[0.003]*		*[0.003]*		*[0.002]*		*[0.005]*	

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Table 6: Continued

	Dependent variable: RAT				
	(2) ***Benchmark model for the values of dummy PAV4 = 0***	*(3)* ***Benchmark model for the values of LBCpca > medianLBCpca***	*(4)* ***Benchmark model for the values of LBCpca ≤ medianLBCpca***	*(5)* ***Benchmark model for the values of dummy South = 0***	*(6)* ***Benchmark model for the values of dummy South = 1***
GRU					
PAV2					
PAV3	0.140 (.0238)	0.233 (.0327)	0.104 (.0185)	0.129 (.0233)	0.259 (.0314)
	[0.098]	*[0.150]*	*[0.125]*	*[0.103]*	*[0.346]*
PAV4					
GDP	0.478*** (.0815)	0.658*** (.0922)	0.231 (.0414)	0.545*** (.0986)	0.296 (.0360)
	[0.168]	*[0.198]*	*[0.383]*	*[0.200]*	*[0.368]*
POP					
DEP					
BADL	0.019*** (.0032)	0.017 (.0023)	0.021** (.0037)	0.036* (.0065)	0.023 (.0027)
	[0.007]	*[0.011]*	*[0.010]*	*[0.018]*	*[0.016]*
UNDERG					
ENFO					
Wald test	303.4	153.0	155.7	284.4	36.23
(df)	15	15	15	15	15
p−value	*0.000*	*0.000*	*0.000*	*0.000*	*0.002*
Pseudo R2	0.229	0.258	0.224	0.239	0.178
Log pseudolikel.	−615.3	−278.2	−350.3	−510.5	−127.1
Observations	2858	1491	1502	2546	447
Firms	2390	1243	1259	2126	376
Credit-rationed firms	219	100	127	179	48

Note: For the description of the variables, see Table 2. The benchmark model is the parsimonious model with bootstrapped SEs (column 7 of Table 5). In square brackets are reported the bootstrapped standard errors (1000 replications), whereas in round brackets are reported the estimated marginal effects. Constant and time dummies included but not reported. Wald statistic tests the null hyphotesis that all the coefficients are jointly zero. The variables TAB, KB, TA, BDEBT, ROA, LIQUI, DEP and BADL are lagged once. Besides, TAB, KB, TA, POP, GDP, DEP and UNDERG are in natural logarithms.

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all the variables, which are not statistically significant in column 2 of Table 5 and present at least one correlation coefficient greater than 0.70 – namely TAB, POP, DEP and UNDERG. The estimation results obtained (column 3, Table 5) confirm the conclusions discussed above.

Then, moving from the specification in column 3, we select the most parsimonious model by a general to simple search: we drop the most insignificant regressor and re-estimate the model until we are left only with explanatory variables that are statistically significant at 10 per cent level. The specification obtained is shown in column 4 of Table 5, which also reports – in round brackets – the explanatory variables' marginal effects. Figures in this column once more confirm the statistical relevance of NBAN, MAIN and KB.

Further, considering the most parsimonious model, we control for banking market level shocks by allowing for within-zone correlation of the error terms over time; in other words, we cluster observations at the province level. The resulting standard errors are also robust to heterosked-asticity. Then, we cluster observations at the firm level. The results of these estimations showed in columns 5 and 6 of Table 5 confirm the significance of the explanatory variables aforementioned.

Moreover, as Appendix A makes explicit, the *H-statistic* represents a generated regressor. Hence, the presence of the local banking competition index among our explanatory variables calls for caution in evaluating the relative inference (Pagan, 1984). We address this point by applying the non-parametric bootstrap method that allows us to estimate the distribution of the parameters by re-sampling (with replacement) the data. More precisely, the probit model bootstrapped standard errors reported in column 7 of Table 5 are obtained by re-sampling the observations 1000 times.[15] Our main results remain, once again, unaltered.

Finally, based on this benchmark model – the most parsimonious model with bootstrapped standard errors reported in column 7 of Table 5 – we perform further robustness checks by modifying our sample according to the following criteria. First, we drop all firms belonging to science-based sector (PAV4), which may be systematically different from the other sample firms as they are generally more opaque and, consequently, prone to be credit-rationed. The results obtained, reported in column 2 of Table 6, confirm those in Table 5. Secondly, we split the dataset according to provinces characterized by high and low competition among banks. This allows the coefficients of all explanatory variables to differ as we move from more to less competitive provinces. To distinguish the higher from the lower competitive local credit markets in the sample, the local banking competition index is averaged across time for each province, and its median

[15] For other authors using this approach to address the generated regressors issue see, for instance, Agostino and Trivieri (2008).

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is considered to individuate two estimating sub-samples. The first one includes all the observations for which the competition index is higher than the median. The second group is made up of all the remaining observations, for which the index is lower than the median. The estimates for the former sub-sample are reported in column 3 of Table 6. These figures are in line with our main conclusions. Besides, the marginal effects of all the significant determinants of interest (NBAN, MAIN, KB) are larger in absolute value compared to those obtained when using the whole sample (column 4, Table 5).

A different picture emerges when looking at column 4 of Table 6, which reports the estimates for the low-competition sub-sample: now, none of our coefficients of interest is found statistically significant. Finally, we run separate regressions for northern and southern regions (see columns 5 and 6 of Table 6). In the former case, the main difference in comparison to column 4 of Table 5 is that the estimated coefficient of MAIN is no longer significant, whereas – for the southern regions – only the coefficient of NBAN is statistically significant.

To summarize, the sensitivity checks above illustrated mostly confirm the significance of the variables that were statistically significant in the first estimation: the number of banks from whom firms borrow, the amount of credit received from the main bank, and banks' equity. This provides evidence that multiple banking relationships and banking market size affect the probability of being credit-rationed for Italian SMEs. On the other hand, the local competition index and firms' capability collateralize never display statistical significance.

5. Conclusions

In this paper we seek to empirically assess which determinants of the capability and incentives of banks to screen and monitor firms are significant in explaining credit rationing to Italian SMEs. In doing so, we do not neglect to control for many other factors at firm level (i.e. firms' riskness) and at banking market level (i.e. aggregate credit riskness), which might influence the phenomenon under study. Besides, also institutional characteristics are taken into account, through some measures of judicial system efficiency and underground economy. After testing for the presence of non-random selection bias and the potential endogeneity of some determinants of interest, the results we obtain indicate that average banking size and multiple banking relationships are statistically significant factors affecting credit rationing, presumably through their impact on the banks' capability and incentives to perform monitoring and screening activities. Other potential determinants of banks' incentives to monitor and screen, such as local banking competition and firm's capability to collateralize are never

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significant. Nevertheless, when we split the sample according to the level of banking competition, we find that none of the aforesaid determinants is statistically significant in the less competitive banking markets. On the other hand, in the more competitive markets, the estimated marginal impacts of all the significant determinants of interest are larger in absolute value than those obtained for the entire sample. These results may represent a first step for further research, as they suggest that local banking competition may affect the impact on the credit rationing phenomenon exerted by multiple banking relationship and banks' size, these latter appearing to be relevant where banks' competitiveness is more vigorous. Two interesting lines of investigation could be developed. The first one could compare the evidence found in the present work with that obtained when considering alternative measures of credit rationing not based on survey data. The second line of research could extend the sample to European SMEs in order to verify whether, when compared to other countries, the determinants of banks' incentives to screen and monitor have heterogeneous effects according to the level of competition in credit markets.

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Appendix A

As noted in Section 3, we obtain our index of local banking competition by Principal Component Analysis of two indicators of competition

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measured at provincial level: the *Herfindahl-Hirschman Index* (HHI) and the non-structural Panzar and Rosse (PR, 1987) *H*-statistic.

Because in Italy, as in most of Europe, data at local bank branch level are not publicly available, we follow Carbò Valverde *et al.* (2003) and Agostino and Trivieri (2008) and draw each variable x we need in the computation of the local banking competition measures as:

$$x_{ipt} = X_{it}{}^{*}\,(BR_{ipt}/BR_{it}) \tag{A.1}$$

where: $i = 1, \ldots, N$; $p = 1, \ldots, 103$; $t = 1995, \ldots 2003$; x_{ipt} is a variable of interest for each branch office of bank i in province p in year t; X_{it} is the same variable of interest as it is shown in the balance-sheet of bank i in year t; BR_{ipt} is the number of branch offices of bank i in province p in year t; BR_{it} is the total number of branch offices of bank i in year t. Then, for each year, we obtain our two local banking competition indicators as follows:

$$HHI_p = \sum (ms_{ip})^2 \tag{A.2}$$

where $ms_{ip} = (D_{ip}/D_p)$ is the deposit market share [16] for each branch office of bank i in the province p, and $D_p = \sum_i D_{ip}$,

$$PR_p = \beta_1 + \beta_2 + \beta_3 \tag{A.3}$$

where the β values are obtained by estimating the following model:[17]

$$\begin{aligned} \log TGR_{ip} &= \alpha + \beta_1 \log UPL_{ip} + \beta_2 \log UPC_{ip} + \beta_3 \log UPF_{ip} \\ &\quad + \beta_4 \log TA_{ip} + \beta_5 \log LTA_{ip} + \beta_6 \log DTF_{ip} + \varepsilon_{ip} \end{aligned} \tag{A.4}$$

All the variables in equations (A.2) and (A.4) are described in Table A.1. The same criterion set forth here was used also to compute TAB and KB.

[16] Petersen and Rajan (1995, p. 418) maintain that the Herfindahl index for deposits is a good proxy for competition in loan markets if the empirical investigation involves firms that largely borrow from local banks, i.e. the credit market for these firms are local. As we note in Sections 1 and 3, this is the case for our sample units.

[17] The specification of this model is close to that used by De Bandt and Davis (2000). On the formal derivation of the *H* statistic, see Panzar and Rosse (1987) and Vesala (1995).

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Table A.1: Description of Variables Used in the Calculation of Local Banking Competition Indicators

Variable		Description
D	Deposits	Customer deposits
GIR	Gross Interest Revenues	Interest received
IBS		Income from banking services
TGR	Total Gross Revenues	GIR + IBS (exceptional items excluded)
TA		Total assets
UPL	Unit Price of Labour	Personnel expenses to number of employees
UPC	Unit Price of Capital	[Physical capital expenditure (depreciation, write-down on intangible and tangible assets) + other operating expenses (exceptional items excluded)] to fixed assets
UPF	Unit Price of Funds	Total interest paid to total funds, where total funds = customer deposits + interbank deposits + money market liabilities, the latter including subordinated debt
LTA		Total loans to total assets
DTF		(Customer deposits + interbank deposits) to total funds

Non-technical Summary

In a hypothetical world of perfect screening and monitoring by banks, no firm should be rationed and each borrower should pay the *right* price to get the loan. But, as shown in the economic literature, banks may differ both in their capability and in their incentive to screen and monitor borrowers. Thus credit rationing may occur. In fact, it seems reasonable to expect that – other things being equal – when banks' screening and monitoring is greater, so is also the probability of gauging the risk of default for each borrower or loan. In turn, borrowers are less likely to be credit-rationed, as the bank can attach the appropriate interest rate to each loan. In other words, it is plausible to estimate that what affects the screening and monitoring capability/incentives of banks might influence firms' credit rationing.

On the basis of this hypothesis, in our study we aim to empirically assess which determinants of banks' capability and incentives to screen and monitor firms are significant in explaining credit rationing to Italian small and medium sized firms (SMEs). For the latter, which make up more than 80 per cent of all manufacturing firms in Italy, loans are almost the only external financial source.

We conduct our empirical analysis at local credit market (provincial) level, and – building on the major literature in the field – focus on banks' size as the main determinant of banks' capability to screen and monitor firms. Furthermore, we contend that banks' incentives to perform the same activities are mainly affected by banking competition, multiple banking

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relationships and a firm's capacity to collateralize. We expect that the greater the banks' size, the higher are banks' screening and monitoring – and the lower is credit rationing. On the other hand, we do not have a clear-cut prediction about banking competition, because the latter may have beneficial effects on credit supply – but may also weaken the incentive to screen and monitor borrowers, with detrimental effects on credit to firms. Furthermore, multiple banking relationships may reduce the incentive to screen and monitor – because each bank bears the full cost of these activities, but must share their benefits with the other lenders. Accordingly, we expect that the higher the number of banks lending to a single firm, the lower each one's incentive to screen and monitor, and the greater credit rationing. Finally, the literature on the topic shows that collateral requirements may actually eliminate credit rationing – but they may also weaken banks' incentive to screen and monitor projects and applicants, hence increasing credit rationing. Thus, with respect to the sign of the relation between firm's collateral and credit rationing, we do not have a clear *a priori* expectation.

In our analysis we also take into account other aspects – both at firm and provincial level – that may influence the relationship between the aforesaid determinants and the credit-rationing phenomenon. At firm level, we consider: size, age, risk, debt, profitability, liquidity, group membership and industrial sectors. At provincial level, we take account of: real gross domestic product, population, deposits, credit market risk, underground economy and legal enforcement in the area.

We carry out our empirical investigation by using a valuable dataset on Italian SMEs (provided by Capitalia, one of the biggest Italian banking groups) and employing an econometric methodology that is appropriate when dealing with a discrete phenomenon, as credit rationing is.

The main results obtained from our study may be summarized as follows. In line with our expectation, the probability of a firm being credit-rationed seems: (i) lower, the higher the average bank size in local markets is; (ii) higher, the greater the number of banks with which the firm has relationships and the percentage of firm's lending with the main bank. On the other hand, the results do not indicate a significant impact of local banking competition and firms' capacity to collateralize on credit rationing. Furthermore, we also find that a larger firm size has a negative effect on the probability of being credit-constrained. A similar result is found for AGE: an older firm seems to be less rationed, even though this negative effect turns into positive for the oldest sample firms. Finally, more riskier and indebted firms display a higher probability of being rationed, whereas better performance indicators (profitability and liquidity) seem to lower this probability.

Our main findings are substantially confirmed when extensive checks were performed to test the results' robustness. Only when splitting the

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firms' sample according to the level of banking competition do we find that none of our determinants of interest is statistically significant in the less competitive banking markets. On the other hand, in the more competitive markets, the estimated impacts of the same determinants are larger in absolute value than those obtained for the entire sample. These interesting results may represent a first step for further research, as they suggest that local banking competition may affect the impact exerted by multiple banking relationships and banks' size on the credit-rationing phenomenon. The above variables appear to be relevant where banks' competitiveness is more vigorous. Two appealing lines of investigation could be developed. The first one could compare the evidence found in the present work with that obtained when considering alternative measures of credit rationing, not based on survey data. The second line of research could extend the sample to European SMEs in order to verify whether, compared to other countries, the determinants of banks' incentives to screen and monitor have heterogeneous effects according to the level of competition in credit markets.

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