BANKING COMPETITION AND BANK FINANCING. EVIDENCE FROM THE ITALIAN MANUFACTURING SMES.

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ABSTRACT. This work investigates whether local differences in banking competition impact on the amount of bank debt used by Italian small and medium sized manufacturing firms. Sample selection and double hurdle models are adopted as the process, which results in the choice of bank financing may differ from that determining its amount. Our main finding is that more competitive banking markets seem to be associated with relatively higher usage of bank debt by less transparent firms. On the other hand, a higher banking competition seems to have no effect on the probability of receiving bank loans (*95 words*).

JEL code: G21; G30.
Key words: bank debt; local banking competition; small and medium sized firms.

1. INTRODUCTION [*]

Increasing time and effort have lately been devoted to empirically investigate the impact of bank competition on firms' access to credit. Such an interest has been driven by the failure of the existing theoretical models to provide univocal predictions on the issue. In this work, we use a large set of microdata to test whether local banking competition affects both the probability and the amount of bank financing that Italian firms employ. We focus attention on SMEs, which have little access to capital markets (either public equity or bond market) and are bound to ask credit to banks having branches in the same local market where they operate. Consistently with other contributions on the Italian banking market, we define 103 local markets corresponding to the existing administrative provinces. As Bonaccorsi di Patti and Dell'Ariccia (2004) highlight, this disaggregation enables us to take advantage of an important feature of the Italian case. Indeed, Italian provinces are characterized by different banking structures and this provides sufficient cross-sectional variability within a single institutional framework. Building upon previous studies, we recover some measures of local banking competition, such as the Herfindahl-Hirschman Index on deposits (HHI), and the Panzar and Rosse (1987) *H* statistic. We then employ these indexes as explanatory variables in two regression models: one aimed at estimating the probability that a small-medium sized firm employs bank debt as a source of financing, the other analyzing the amount of this kind of financing. A distinguishing feature of our analysis is that it allows correlation between these models and takes into account the censored nature of the dependent variable. In other words, instead of estimating separate regressions, as most empirical studies do, we adopt double hurdle and type II tobit (alias sample selection) models to shed light on the relationship between bank competition and access to credit in the Italian provinces. In particular, we investigate whether this relationship varies across firms of different age, and, more generally, of different opaqueness by constructing an index of firm transparency. The econometric strategy, the use of both structural and non-structural indicators of local banking competition and the measures of firm opaqueness that we employ represent the main distinctive aspects of our paper with respect to the extant literature in the field.

The remainder of the paper is organized as follows: section 2 presents a brief review of the relevant literature; section 3 summarizes the main approaches we adopt in measuring banking competition and specifies the econometric models we employ; section 4 describes the data; section 5 reports the results that are obtained and the robustness checks that are performed; section 6 concludes.

2. THE ECONOMIC ROLE OF BANKING COMPETITION: A BRIEF REVIEW OF THE LITERATURE

The economic effects of banking competition have become an important issue for debate in the literature in recent years, leading to a considerable number of works both on the theoretical and empirical field. Broadly speaking, these studies can be grouped into three blocks.[1]

The first one includes the contributions which support the neoclassical approach. It claims that in the banking industry - as in every other economic sector - lower competition leads to welfare losses, as banks with higher market power charge higher interest rates on loans and pay lower interest rates on deposits (see - among others - Pagano, 1993 and Guzman, 2000). This conventional wisdom has been recently challenged by several theoretical studies raising doubts on the overall beneficial welfare impact of banking competition. Building upon the pioneering work of Stiglitz and Weiss (1981), these contributions em-

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[1] In the following we focus on the research which has directly investigated into the economic effects of banking competition. We do not take explicitly into account the numerous studies that have analyzed the effects on banking competition of consolidation waves, an aspect that - in the last two decades - has characterized the banking industry of many countries. For reviews of such contributions see - among others - Berger et al. (1999), Carletti et al. (2002), Northcott (2004), Degryse and Ongena (2005).

phasize the role of asymmetric information problems in the relationships between lenders and borrowers, and show that credit rationing can be an equilibrium outcome in competitive lending markets. In perhaps the most widely cited article belonging to this research line, Petersen and Rajan (1995) prove that younger firms may receive more credit, and at better rates, if they are in a market where bank monopoly power is relatively higher. In a model of bank screening, Shaffer (1998) shows that the average quality of a bank's pool of borrowers declines as the number of competitors in a banking market raises, while Dell'Arriccia (2000) demonstrates that the higher is the number of banks in a market the lower is the likelihood that they screen entrepreneurs as opposed to lending indiscriminately. Between the studies belonging to the two approaches so far mentioned (referred to as *structure-conduct-performance hypothesis* and *information-based hypothesis*, respectively) there are other contributions which present mixed theoretical conclusions. For example, Cetorelli (1997) and Cetorelli and Peretto (2000) find that, as the conventional wisdom suggests, there is a positive relationship between number of banks in a market and quantity of credit available to entrepreneurs; however, banks' incentives to screen are positively linked to their monopoly power.

On a pair with the theoretical research, the empirical works dealing with the economic effects of banking competition reach mixed conclusions too. According to Jayaratne and Strahan (1996) estimates, both U.S. personal income and output growth accelerated after branching deregulation, thus providing (indirect) evidence in favour of the beneficial effects of banking competition. Black and Strahan (2002) use cross-industry, cross-state U.S. data, and find that the number of new firms and new business incorporations is smaller in states where bank monopoly power is higher. On the other hand, there are several studies that provide evidence of negative effects related to competition among banks. In their already mentioned contribution, Petersen and Rajan (1995) analyze credit availability for a cross-section of U.S. small firms located in markets with different degrees of banking concentration and find that - where the latter is higher - firms have both less credit constraints and pay lower loan rates (thus granting support to their theoretical thesis). Also Shaffer (1998) presents evidence of higher loan charge off rates in MSAs (Metropolitan Statistical Areas) where higher is the number of banks. Bonaccorsi di Patti and Gobbi (2001) use Italian cross-province data [2] and show that entry has a significant negative effect on lending to small firms and no effects on bad loans. By using cross-industry, Italian cross-province data, Bonaccorsi di Patti and Dell'Ariccia (2004) investigate the effect of banking concentration on the rate of creation of new firms. They find that this effect is positive and is stronger for firms belonging to industry sectors that are more informationally opaque.

Finally, there are some empirical papers which show that banking market structure may have multiple effects on the economy, both positive and negative, making it hard to establish which one ultimately dominates (Cetorelli, 2001). By using data on 36 industry sectors in 41 countries, Cetorelli and Gambera (2001) evaluate the role of banking market structure on growth across industries. They reach two main conclusions: on the one hand, bank concentration has on average a depressive effect on industry growth; on the other hand, industries more dependent on external finance grow relatively faster in those countries where the banking sector is more concentrated, and the beneficial effect of bank concentration is more pronounced for younger firms than for the mature ones.

The controversial results obtained in the literature on the economic effects of bank market power call for further research. Our paper aspires to throw new light on this topic by empirically investigating the relationship between banking competition and the usage of bank debt by SMEs in Italy.

3. EMPIRICAL QUESTION AND METHODOLOGY

According to models such as Petersen and Rajan's (1995), relatively more competitive banking markets should be associated with relatively less credit to informationally opaque firms. This work intends to test this prediction with regard to the Italian SMEs, for which bank debt represents the dominant source of external financing (see Cesarini, 2003). In order to carry out this test, we first compute some measures of banking competition at the province level. Then, we interact them with a measure of firm opaqueness. Finally, we investigate whether these two variables significantly affect the probability that a small firm employs bank debt as a source of financing, and the amount of this kind of financing.

3.1 Measuring bank competition

We measure local banking competition (LBC) at provincial level by using both a structural index, the Herfindahl-Hirschman Index (HHI), and a non-structural indicator, the Panzar and Rosse (1987) *H* statistic (PR). Since in Italy, like in most European countries, data at local banking office level are not publicly available, we follow Carbò Valverde et al. (2003) and draw each variable x we need in the computation of the LBC measures as: $x_{ipt} = X_{it} * (BR_{ipt} / BR_{it})$, where: $i=1,\dots,N$; $p=1,\dots,103$; $t=1995,\dots 2000$; 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 provided by 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 that is considered in the analysis, we obtain our two LBC indicators as follows: (1) $HHI_p = \sum (ms_{ip})^2$, where $ms_{ip} = (D_{ip} / D_p)$ is the market share on deposits [3] for each branch office of bank i in the province p, and $D_p = \sum_i D_{ip}$; (2) $PR_p = \beta_1 + \beta_2 + \beta_3$ where the β values are obtained by estimating the following model: [4]

$$\log TGR_{ip} = \alpha + \beta_1 \log UPL_{ip} + \beta_2 \log UPC_{ip} + \beta_3 \log UPF_{ip} + \beta_4 \log TA_{ip} + \beta_5 \log LTA_{ip} + \beta_6 \log DTF_{ip} + \varepsilon_{ip}$$

[2] An Italian province may be compared to a U.S. MSA.

[3] The HHI is computed on deposits only (and not on loans) given that depositors typically have less market power than borrowers.

[4] 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), whereas for an extensive literature review of the studies that - starting with Shaffer (1981a, 1981b, 1982) - apply this statistic to the banking industry, see Koutsomanoli-Fillipaki and Staikouras (2004).

All the variables here employed are described in Table 1.

3.2 The econometric models

Type I tobit model. Our dependent variable is the ratio of bank loans with respect to the total assets. This variable is zero for a substantial part of the population, and is essentially continuous over positive values. In other words, there is a mass point at zero because many individuals find a corner solution optimal. The most commonly used method in this case is the tobit model. Since we use panel data, we apply the following pooled tobit model: $y_{it} = x'_{it}\beta + \varepsilon_{it}$ if $b^*_{it} = x'_{it}\beta + \varepsilon_{it} > 0$ and $y_{it} = 0$ if $b^*_{it} = x'_{it}\beta + \varepsilon_{it} \leq 0$ where $\varepsilon_{it} \sim N(0,\sigma^2)$. The density of the observed variable *y* is the same as the density of the latent variable b^* over positive values, whereas it collapses to zero (the mass point) when $b^* < 0$. [5] This model, however, posits some limitations. Indeed, the same vectors of variables *x* and coefficients β determine both the probability that an observation is censored and the level of the dependent variable. In many circumstances where there are fixed costs of moving away from the mass point, this is not the case. Fixed costs arise when individual resources must be devoted a priori to the participation decision irrespective of transaction quantities.

In this study, adopting a tobit model implies that the same (observable and unobservable) variables that drive the decision of addressing a bank for finance determine the amount that a firm obtains. In fact, there might exist fixed costs in choosing bank financing, which may derive from banking market structure and development or from firms characteristics. Recent contributions on financing patterns around the world and financial relations between banks and firms assume the following two-step process in relation to how firms decide their external financing (see, i.e., Beck et al. 2002, and Hori and Osano, 2003). First, the managers choose a particular source of financing. Next, they decide the proportion of investment to finance through that source. Consistently with this assumption, they advocate the use of sample selection or double hurdle models.

Double hurdle model. To overcome the tobit shortcomings, a double hurdle model is adopted, where the determinants of selection and amount may differ, or a given set of determinants may have different levels of relative importance. This allows greater flexibility and theoretical development in our test on bank competition and bank financing to SMEs. The name of this class of models - initially introduced by Cragg (1971) - comes from the idea that individuals must overcome two separate hurdles before they are observed with a positive level of consumption. Participation and consumption are treated as two individual decisions, which in Cragg's model are independent. Two latent variables models are employed: a probit for the participation and a truncated model for the expenditure level.

To formalize, the Cragg Independent Model may be represented as follows: $b^*_i = z'_i\alpha + \varepsilon_{1i}$ (*selection equation*) and $y^*_i = x'_i\beta + \varepsilon_{2i}$ (*substantial equation*) where b^*_i and y^*_i are two latent variables, and the error terms are assumed to be independently normally distributed, with $\varepsilon_{1i} \sim N(0,1)$ and $\varepsilon_{2i} \sim N(0,\sigma^2_2)$. The observability criteria are: $y_i = x'_i\beta + \varepsilon_{2i}$ if $b^*_i > 0$ and $y^*_i > 0$, while $y_i = 0$ otherwise. The likelihood function is the product of probit terms for the censored observations and truncated normal density terms for the uncensored observations. Following the logic of this class of models, we assume that firms have to pass a first hurdle in order to get off the mass point and become potential bank borrowers. Given that a firm is a potential bank client, some current circumstances (second hurdle) determine whether or not it does in fact borrow.

Type II tobit model. The Heckman selection model represents an alternative to the hurdle model. As the latter, it allows us to consider the selection as a potentially different process. However, neither it treats selection and outcome processes as independent, nor it requires a double hurdle to be passed. More precisely, the latent variable processes have the following observability criteria: $y_i = x'_i\beta + \varepsilon_{2i}$ if $b^*_i > 0$ and y_i otherwise. Only a hurdle is left ($b^*_i > 0$) and, as selection and outcome processes are not independent, the error terms may be correlated. According to this model: $E[y \mid x, B=1] = x'_i\beta + E[\varepsilon_{2i} \mid x, B=1] = x'_i\beta + E[\varepsilon_{2i} \mid \varepsilon_{1i} > -z'_i\alpha] = x'_i\beta + \rho\sigma\lambda(z'_i\alpha)$, where $\lambda(z'_i\alpha) = \phi(z'_i\alpha)/\Phi(z'_i\alpha)$ is the inverse Mill's ratio. Since α is unknown, Heckman suggests a two-step procedure. Alternatively, the total model may be more efficiently estimated by maximizing the following likelihood function: $L = \prod_{y_i=0} Pr(B_i = 0 \mid z_i) * \prod_{y_i>0} Pr(y_i \mid x_i, z_i, B_i = 1)$, where f is the density function of y_i.

3.3. Empirical specification

In our specification, the dependent variable *y* represents the ratio of total bank debt to total assets. With regard to the explanatory variables, the vectors *z* and *x* consist of regressors, which control for firm, sectoral and local market characteristics. The vector z accounts for firm specific attributes such as size, age, group membership, cash flow, and the ratios of liquid assets, physical assets, and bond debt to total assets. Sectoral dummies are included to control for sub-sector heterogeneity within the manufacturing area. These dummies follow the ATECO 91 classification of the economic lines of business. [6] As far as local market characteristics are concerned, we consider some economic indicators at the province level, such as (the log of) real per capita income, and (the log of) population. Finally, we include year fixed effects, a location dummy for Southern firms, and a dichotomous variable for those benefiting from tax incentives. Further information on these variable is reported in table 2. The vector *x* includes the same control variables, with the exception of the bond debt ratio, and the dummies for

[5] Notice that, by clustering observations at the province level, we make allowance for within zone correlation of the error terms over time.
[6] This classification, provided by ISTAT, identifies 23 sub-sectors within the manufacturing area.

group membership and tax incentives. These variables are assumed to affect only the selection process, and their exclusion from the substantial equation allows us to better identify the models.

Turning to the core of our statistical analysis, a vector *h* is added to both the selection and the substantial equations. This vector consists of two terms: a measure of bank competition at the province level (HHI or PR) and its interaction with a measure of firm opaqueness, which is the firm age (as older companies are less difficult to assess, given their longer records). We employ age rather than another measure of opaqueness, such as firm size, since in our sample only 3.5% of the observations concern medium sized firms employing from 101 to 250 workers, the remainder consisting of small sized firms employing up to 100 workers. However, as a robustness check, we consider firm age together with firm size and another measure of opaqueness *à la* Bonaccorsi di Patti and Dell'Ariccia. More precisely, by using a principal component analysis (PCA), we build a transparency index out of age, size and a measure of opaqueness at the sectoral level (see subsection 5.1).

4. DATA

This work uses four main datasets. Information on Italian manufacturing firms is drawn from Capitalia's 7^{th} and 8^{th} surveys, known as *Indagini sulle Imprese Manifatturiere*, covering the period from 1995 to 2000. As we focus our attention on SMEs, we drop firms with more than 250 workers and those with shares listed on the Stock Exchange. Since several firms (3345) are not included in the first survey, the panel we employ turns out to be unbalanced. A second data source is BILBANK 2000 - edited by the Italian Banking Association (ABI) - which provides the balance-sheet data on almost all the Italian banks. A third dataset, provided by the Bank of Italy, gives us figures on the territorial distribution of branches for each Italian bank. Finally, we draw some variables - such as population and per capita income - from the ISTAT, to control our estimates for local market characteristics. Table 2 describes all the variables that are employed in the estimations, while table 3 reports their summary statistics. Notice that the different availability of data on different variables restricts the estimation sample to 9817 observations on 3804 firms, whose large majority consist of SMEs employing up to 100 workers.

5. RESULTS

Table 4 shows the tobit estimates of model 1. The column labeled LBC=HHI reports the estimates obtained by employing the Herfindahl Index as the measure of local banking competition, while the column LBC=PR shows those that are obtained when using the Panzar and Rosse indicator. Standard errors (not reported) are corrected for clustering at the province level, and the p-values are reported beside the coefficient estimates. To begin with, both regressions appear to be highly significant, as the Likelihood Ratio (LR) test is statistically significant at any conventional level.[7] Our measures of banking competition, and their respective interaction terms, are statistically significant only in the HHI column. A consistent pattern, however, emerges already. The HHI and its interaction term coefficients display the opposite signs of the corresponding PR coefficients. This pattern is consistent as the two measures express opposite degrees of local banking competition: the higher is the Herfindahl Index, the lower is the competition, whereas the higher is the Panzar and Rosse, the higher the competition.

To take the analysis a step further, we now allow the determinants of selection and bank debt amount to differ, or to have different levels of relative importance. Indeed, as the tobit is nested in the double hurdle model, we can compare the former against the latter through a Likelihood Ratio test (Model test). This turns out to be highly significant, thus rejecting the tobit formula. Table 5 reports the double hurdle model estimates. Both measures of banking competition (and their respective interaction terms) are now both individually and jointly significant in the main equation.[8] Their signs are the same as in the tobit case, and may be interpreted as follows: the lower is the banking competition, the lower is the amount that firms borrow from banks. This negative impact, however, depends on the level of firm opaqueness. For older (i.e. less opaque) firms this impact tends to decrease in absolute value and turns into positive. In other words, according to our estimates, relatively less competitive banking markets are associated with relatively more credit to more transparent firms. At first glance, this result appears not to be in line with models such as Petersen and Rajan's (1995). Turning to the selection equation, the vector *h* is not significant, thus banking competition seems to have no impact on the probability of obtaining a loan.

5.1 Robustness checks

First, we address the robustness of our results to the methodology that is employed. To this aim, we estimate a Heckman selection model, which substantially confirms the double hurdle model results. As table 6 shows, both measures of banking competition and their interaction terms maintain their signs and significance in the outcome equation, except for the *H* statistic, which loses its individual significance. As far as the robustness checks on the specification we adopt are concerned, results do not change when we take into account other potential control variables such as the riskness of the local banking market (proxied by the ratio of bad loans on total loans, computed at the province level), the branch density (number of branches to total province population, multiplied by 10000), and the local employees. Similarly, results remain substantially unaltered when we replace some controls with other ones (for instance, we replace the log of the total assets with the log of sales), and re-run all regressions by using the lagged values of the measures of banking competition and opaqueness, so as to mitigate any potential simultaneity bias. These results are not reported in order to avoid cluttering, but they are available from the au-

[7] With regard to the significant control variables, a larger size and tax incentives positively affect both the probability of receiving and the amount of bank loans. By contrast, larger amounts of cash flow, liquid assets, and belonging to a group seem to decrease the probability and amount of bank loans. Furthermore, a larger local population is associated with a lower probability and amount of bank debt, while the opposite is true for the per capita income variable.

[8] A caveat is here with respect to the *H* statistic, as this variable represents a "generated regressor" (see Pagan, 1984) that may be problematic for the inference on the other regressors.

thors upon request. Furthermore, in order to check the sensitivity of our results to the particular measure of opaqueness that is employed, we build an index of firm transparency summarizing the influence of age, size (proxied by total assets) and a measure of transparency at the sectoral level.[9] When considering this transparency index, we also employ an index of local banking competition based on the PR indicator and (the complement to one of) the HHI.[10] Both the transparency (TRANSP-pca) and banking competition (LBCpca) indexes are constructed by using a principal component analysis, which is intended to minimize the arbitrariness implied by the aggregation method.[11] As table 7 illustrates, our main results remain substantially unaltered: the local banking competition index displays a positive coefficient, while its interaction term with the transparency index presents a negative coefficient in both the double hurdle and the Heckman estimates. The banking competition index is not individually significant, but it results jointly significant with its interaction term when implementing a Likelihood Ratio test. Finally, a further check is carried out by rebuilding the local banking competition index: an approximation of the Lerner index [12] is employed together with the *H* statistic and the Herfindahl Index. The estimates that are obtained (available from the authors upon request) confirm the same pattern. In addition, the banking competition index is now also individually significant.

6. CONCLUSIONS

This work investigates the relationship between local banking competition and bank debt usage of Italian SMEs by employing a flexible framework capturing the notion that the determinants of incidence and amount of bank loans may differ. Our main finding is that more competitive banking markets seem to be associated with relatively higher usage of bank debt by less transparent firms. More precisely, we find that the higher the banking competition, the higher is the amount that firms borrow from banks. This impact, however, depends on the level of firm opaqueness; for less opaque (e.g. older) firms it tends to decrease. This result appears not to be in line with Petersen and Rajan's (1995) model. Indeed, according to our evidence, it is higher competition that goes to the advantage of informationally opaque borrowers, while - according to Petersen and Rajan's prediction - it is lower competition that gives the incentive to banks to lend to less transparent firms. On the other hand, a lower banking competition seems to have no effect on the probability of receiving a loan. In other words, while the level of competition appears not to affect the probability of receiving bank loans, once this decision has been made the competition level does seem to have an influence on how much credit is obtained.

Thus, our findings concerning the selection equation do not seem to be consistent with a situation where increasing competition leads the banks to loosen the screening process in order to gain new customers. On the other hand, our results concerning the substantial equation may be the consequence of a larger number of banks operating in the markets, which makes it easier for opaque firms to fractionalize their debt among many intermediaries in order to maximize the amount of credit obtained. In such a situation phenomena of free-riding may favour the applicants: banks are more inclined to lend to opaque firms counting on the monitoring activity of the other intermediaries involved. This scenario could be consistent with the multi-banks relationships characterizing the Italian firms practice. As a matter of fact, in Italy borrowing from several banks is a predominant phenomenon, known as "*multiaffidamento*" (see, e.g., Pagano et. al, 1998, and Ongena et al., 2000). An alternative interpretation could be that competitive pressure creates incentives for a greater efficiency in the banking screening process: market discipline might make banks screen better and lend more to young and opaque firms on the basis of the expected performance rather than the past records. Indeed, as claimed by Benfratello et al. (2005, p.13), as a consequence of higher competition banks may “introduce better and more advanced practices in the screening, selection, evaluation and monitoring of projects and entrepreneurs. These practices may include looking more carefully and with better tools to borrowers’ future prospect, as opposed to relying purely on firms’ marketable assets as collateral”.

To shed light on these alternative interpretations, further research is called for on whether firms' performance is different across different banking markets. Indeed, if higher competition is associated with phenomena of free-riding implying less rigorous screening processes, ceteris paribus, higher competition should be associated with firms' worse performance, and vice versa if higher competition is synonymous with better screening processes, more competitive banking market should be correlated to firms' better performance.

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[9] The latter is computed as the ratio of physical assets to total assets for each ATECO manufacturing sub-sector, under the assumption that "industry opaqueness is negatively correlated to the relative use of fixed and tangible assets in the production process adopted in each industry: the larger the share of these assets in the typical firm balance sheet in the industry, the more transparent is the industry" (Bonaccorsi di Patti and Dell'Ariccia, 2004, p. 234). This sub-sectoral ratio is obtained as the yearly mean value of the individual firm ratios.

[10] Considering (1-HHI) allows us to obtain a measure that is homogenous to the *H* statistic, with the consequence that the resulting index behaves as the Panzar and Rosse indicator: higher values express greater banking competition.

[11] The principal component method allows us to describe a set of variables by means of a new set of lower dimensionality. Therefore, it is employed to address the problem of multicollinearity that might result from the presence of a set of highly correlated regressors. The new variables are linear combinations of the original set of variables, where the weights are chosen so as to maximize the variance explained by the composite variable (for a description of this method see Johnston, 1984). In our case, we want to summarize three measures of firm transparency by means of one number that best captures their cumulative effect. Therefore, the first principal component, explaining 40% of the variance, is used. Finally, notice that prior to the PCA, we have standardized our variables in order to avoid that the variable with the highest variance dominates the resulting index.

[12] Following Carbò Valverde et al. (2003), this index is defined as the mark-up of asset price (PTA) over average cost (ACTA) relative to price or (PTA - ACTA) / PTA , and it is computed by using the methodology described in section 3.1. PTA is given by the ratio of total gross revenue (gross interest revenue plus income from banking services) to total assets, while ACTA is the ratio of total operating costs (inclusive of labor costs) and interest costs to total assets. Values of Lerner index greater than one or lesser than zero are assumed to be equal to one and zero respectively. Again, the complement to one of this measure is considered, in order to make the Lerner index homogeneous to the *H* statistic.

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TABLE 1 - Description of variables used in the calculation/estimation of local banking competition indicators

VARIABLE	**DESCRIPTION**
D	Customer deposits
TGR	Total Gross Revenues = GIR + IBS (exceptional items excluded)
GIR	Gross Interest Revenues = Interest received
IBS	Income from banking services
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

TABLE 2 - Description of variables used in the estimations

VARIABLE	**DESCRIPTION**
BANKDEBT	Bank debt on TA
DBANKDEBT	Dummy =1 if BANKDEBT>0, and zero otherwise
HHI	Herfindahl-Hirschman Index on deposits at provincial level *(see sub-section 3.1)*
PR	Panzar and Rosse statistic at provincial level *(see sub-section 3.1)*
LBCpca	Index of local banking competition, constructed by principal component analysis based HHI and PR *(see sub-section 5.1)*
TRANSPpca	Index of firm transparency, constructed by principal component analysis based on AGE, TA, TRANSPateco *(see sub-section 5.1)*
AGE	Current year minus firm's year of establishment
TA	Total Assets
EMPLO 11-20	Dummy=1 if firm has 11-20 employees, and zero otherwise
EMPLO 21-50	Dummy=1 if firm has 21-50 employees, and zero otherwise
EMPLO 51-100	Dummy=1 if firm has 51-100 employees, and zero otherwise
EMPLO 101-250	Dummy=1 if firm has 101-250 employees, and zero otherwise
ATECO_***x***	Dummy =1 if firm belongs to the ***x*** ATECO manufacturing sub-sector (coded with ***x*** from 15 to 37), and zero otherwise *(see sub-section 3.3)*
TRANSPateco	Measure of transparency at the sub-sectoral level computed as the ratio of physical assets on total assets for each ATECO manufacturing sub-sector
TGASS	Property, plant, equipment and land on TA
CASHFL	Net profit plus amounts charged off for depreciation, depletion, and amortization.
LIQUI	Cash, accounts receivable, other current assets on TA
INCEN	Dummy =1 if firm benefits from tax incentives, and zero otherwise.
NORTH	Dummy =1 if firm is located in the North, and zero otherwise
CENTER	Dummy =1 if firm is located in the Center, and zero otherwise
SOUTH	Dummy =1 if firm is located in the South, and zero otherwise
BOND	Bonds debt on TA
GROU	Dummy =1 if firm belongs to a group, and zero otherwise
RPI	Real per capita Income
POP	Population

All the variables of this table are drawn from the 7th and 8th Capitalia's surveys (*Indagini sulle Imprese Manufatturiere*) with the exception of : *i)* HHI, PR and LBCpca obtained by our calculations or estimations on data BILBANK (ABI) and *ii)* RPI and POP which are drawn from ISTAT.

TABLE 3 - Summary statistics

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs**
BANKDEBT	15.3899	17.7563	0.0000	88.6305	13,959
HHI	0.1148	0.0430	0.0454	0.4131	17,090
PR	0.4332	0.3583	-1.4153	1.8554	17,090
LBCpca	0.0000	1.1053	-5.8499	2.9907	17,090
TRANSPpca	0.0000	1.1423	-2.4020	8.2814	13,902
AGE	21.8505	16.0953	0.0000	146.0	16,996
TA *	4,190.9	7,835.6	74.89	95,434	13,959
EMPLO 11-20	0.3760	0.4844	0.0000	1.0000	17,090
EMPLO 21-50	0.3982	0.4896	0.0000	1.0000	17,090
EMPLO 51-100	0.1850	0.3883	0.0000	1.0000	17,090
EMPLO 101-250	0.0408	0.1978	0.0000	1.0000	17,090
TRANSPateco	23.054	4.922	4.066	52.387	17,088
TGASS	23.067	16.024	0.000	91.292	13,959
CASHFL	13.1235	8.3948	-44.522	66.904	13,959
LIQUI	71.792	16.885	2.683	101.137	13,959
INCEN	0.3998	0.4899	0.0000	1.0000	16,940
NORTH	0.6577	0.4745	0.0000	1.0000	17,090
CENTER	0.2036	0.4027	0.0000	1.0000	17,090
SOUTH	0.1387	0.3457	0.0000	1.0000	17,090
BOND	0.4504	2.1192	0.0000	23.5834	13,959
GROU	0.1758	0.3807	0.0000	1.0000	17,063
RPI *	13.452	2.171	7.442	17.304	17,090
POP **	1,096,931	1,107,880	91,350	3,849,487	17,090

* In thousands of Euro. ** In units. All the other variables are expressed in percentage terms. For the description of the variables see Table 2. ATECO dummies not reported.

TABLE 4 - Tobit estimations

	Dependent variable: BANKDEBT			
	LBC = HHI		LBC = PR	
LBC	-108.43***	*(0.0000)*	3.39	*(0.2740)*
INT	33.77***	*(0.0000)*	-1.35	*(0.1850)*
AGE	-2.27**	*(0.0300)*	2.28***	*(0.0000)*
TA	9.86***	*(0.0000)*	9.86***	*(0.0000)*
TGASS	0.04	*(0.2180)*	0.03	*(0.2440)*
CASHFL	-0.73***	*(0.0000)*	-0.73***	*(0.0000)*
LIQUI	-0.06**	*(0.0340)*	-0.06**	*(0.0380)*
INCEN	1.84***	*(0.0000)*	1.84***	*(0.0000)*
SOUTH	0.22	*(0.8720)*	0.16	*(0.9080)*
BOND	0.12	*(0.2560)*	0.12	*(0.2620)*
GROU	-2.85***	*(0.0000)*	-2.90***	*(0.0000)*
RPI	7.66***	*(0.0060)*	7.96***	*(0.0040)*
POP	-1.89***	*(0.0000)*	-1.74***	*(0.0000)*
N. of obs	9817		9817	
censored	3888		3888	
uncensored	5929		5929	
LR chi2	2913.89	*(0.0000)*	2897.94	*(0.0000)*
Log likelihood	-29602.15		-29610.13	

In italics are reported the p-values of the tests. The t statistics (not reported) are corrected for clustering on provinces. (*), (**), (***) denote statistical significance at the 10%, 5% and 1% level, respectively. LBC is a measure of local banking competition, either HHI or PR. INT is the interaction term between LBC and AGE. The variables AGE, TA, TGASS, INCEN, RPI and POP are in natural logarithms. With the exception of HHI, PR, AGE, SOUTH, POP and the sectoral dummies, all the explanatory variables are lagged one year. The estimated coefficients of the constant term, time and sectoral dummies (ATECO) are not reported. For further description of the variables see Table 2.

TABLE 5 - Double Hurdle estimations

Substantial Equation. Dep. variable: BANKDEBT				
	LBC = HHI		**LBC = PR**	
LBC	-105.87***	*(0.0060)*	7.37*	*(0.0620)*
INT	33.67***	*(0.0040)*	-2.37**	*(0.0470)*
AGE	-3.78**	*(0.0130)*	1.25	*(0.1880)*
TA	1.64***	*(0.0000)*	1.62***	*(0.0000)*
TGASS	0.05	*(0.3780)*	0.05	*(0.3960)*
CASHFL	-1.00***	*(0.0000)*	-1.01***	*(0.0000)*
LIQUI	-0.14***	*(0.0100)*	-0.14***	*(0.0090)*
SOUTH	-4.71*	*(0.0570)*	-4.95*	*(0.0510)*
RPI	3.69	*(0.4910)*	3.27	*(0.5530)*
POP	-1.70**	*(0.0110)*	-1.69**	*(0.0140)*
Selection Equation. Dep. variable: DBANKDEBT				
	LBC = HHI		**LBC = PR**	
LBC	-0.50	*(0.8260)*	-0.07	*(0.7410)*
INT	0.16	*(0.8420)*	-0.02	*(0.8190)*
AGE	0.09	*(0.3600)*	0.11*	*(0.0650)*
TA	0.97***	*(0.0000)*	0.98***	*(0.0000)*
TGASS	-0.01**	*(0.0420)*	-0.01**	*(0.0370)*
CASHFL	0.02***	*(0.0000)*	0.02***	*(0.0000)*
LIQUI	0.00	*(0.3680)*	0.00	*(0.3590)*
SOUTH	0.32*	*(0.0500)*	0.33**	*(0.0480)*
RPI	0.31	*(0.3490)*	0.35	*(0.2830)*
POP	-0.02	*(0.7420)*	-0.01	*(0.8380)*
INCEN	0.03	*(0.5570)*	0.03	*(0.5460)*
BOND	0.52***	*(0.0000)*	0.53***	*(0.0000)*
GROU	0.18**	*(0.0280)*	0.18**	*(0.0250)*
N. of obs	9817		9817	
censored	3888		3888	
uncensored	5929		5929	
Log Likel.	-28851.67		-28857.26	
Model Test	1500.96***	*(0.0000)*	1505.73***	*(0.0000)*

TABLE 6 - Heckman estimations

Substantial Equation. Dep. variable: BANKDEBT				
	LBC = HHI		**LBC = PR**	
LBC	-109.07***	*(0.0010)*	5.63	*(0.1110)*
INT	34.95***	*(0.0000)*	-1.87*	*(0.0800)*
AGE	-3.63***	*(0.0060)*	1.32	*(0.1470)*
TA	3.32***	*(0.0010)*	3.37***	*(0.0010)*
TGASS	0.01	*(0.8080)*	0.01	*(0.8530)*
CASHFL	-0.82***	*(0.0000)*	-0.83***	*(0.0000)*
LIQUI	-0.13***	*(0.0010)*	-0.13***	*(0.0010)*
SOUTH	-2.79	*(0.2110)*	-2.90	*(0.2030)*
RPI	5.15	*(0.2570)*	5.02	*(0.2810)*
POP	-1.60***	*(0.0030)*	-1.57***	*(0.0040)*
Selection Equation. Dep. variable: DBANKDEBT				
	LBC = HHI		**LBC = PR**	
LBC	-2.43	*(0.2390)*	0.12	*(0.4970)*
INT	0.65	*(0.3320)*	-0.06	*(0.2850)*
AGE	0.06	*(0.4580)*	0.17***	*(0.0000)*
TA	0.70***	*(0.0000)*	0.69***	*(0.0000)*
TGASS	0.00	*(0.2670)*	0.00	*(0.2730)*
CASHFL	-0.02***	*(0.0000)*	-0.02***	*(0.0000)*
LIQUI	0.00	*(0.2490)*	0.00	*(0.2690)*
SOUTH	0.11	*(0.3770)*	0.11	*(0.3910)*
RPI	0.24	*(0.3040)*	0.27	*(0.2690)*
POP	-0.06*	*(0.0840)*	-0.05*	*(0.0820)*
INCEN	0.09**	*(0.0250)*	0.09**	*(0.0270)*
BOND	0.04***	*(0.0010)*	0.04***	*(0.0010)*
GROU	0.11*	*(0.0520)*	0.12**	*(0.0470)*
N. of obs	9817		9817	
censored	3888		3888	
uncensored	5929		5929	
Log Likel.	-29400.07		-29411.38	
Wald test	867	*(0.0000)*	894	*(0.0000)*
Lambda	9.21**	*(0.0028)*	9.49**	*(0.0029)*

TABLE 7 - Robustness

Substantial Equation. Dep. variable: BANKDEBT				
	LBC = HHI *Double Hurdle*		**LBC = PR** *Heckman*	
LBCpca	0.33	*(0.3190)*	0.30	*(0.2950)*
INT	-0.54**	*(0.0350)*	-0.66***	*(0.0010)*
TRANSPpca	0.79*	*(0.0520)*	2.00***	*(0.0010)*
TA				
TGASS	0.01	*(0.8290)*	-0.02	*(0.5970)*
CASHFL	-1.07***	*(0.0000)*	-0.90***	*(0.0000)*
LIQUI	-0.19***	*(0.0010)*	-0.17***	*(0.0000)*
SOUTH	-5.22**	*(0.0370)*	-3.07	*(0.1880)*
RPI	2.11	*(0.6940)*	3.79	*(0.4320)*
POP	-1.63**	*(0.0150)*	-1.69***	*(0.0020)*
Selection Equation. Dep. variable: DBANKDEBT				
	LBC = HHI		**LBC = PR**	
LBCpca	-0.03	*(0.3130)*	0.00	*(0.8870)*
INT	-0.02	*(0.5070)*	0.00	*(0.9970)*
TRANSPpca	0.75***	*(0.0000)*	0.45***	*(0.0000)*
TA				
TGASS	-0.01*	*(0.0830)*	-0.01*	*(0.0790)*
CASHFL	-0.01	*(0.1290)*	-0.03***	*(0.0000)*
LIQUI	-0.01	*(0.2490)*	-0.01***	*(0.0040)*
SOUTH	0.36***	*(0.0090)*	0.13	*(0.2730)*
RPI	0.20	*(0.4910)*	0.11	*(0.6310)*
POP	-0.05	*(0.2640)*	-0.07**	*(0.0130)*
INCEN	0.29***	*(0.0000)*	0.23***	*(0.0000)*
BOND	0.76***	*(0.0020)*	0.06***	*(0.0000)*
GRU	0.51***	*(0.0000)*	0.40***	*(0.0000)*
N. of obs	9817		9817	
censored	3888		3888	
uncensored	5929		5929	
Log Likel.	-29400.01		-29983.6	
Wald test			817	*(0.0000)*
			9.35**	*(0.0008)*

In italics are reported the p-values of the tests. The z statistics (not reported) are corrected for clustering on provinces. (*), (**), (***) denote statistical significance at the 10%, 5% and 1% level, respectively. In tables 5 and 6, LBC is the measure of local banking competition, either HHI or PR, and INT is the interaction term between LBC and AGE. The Model Test in table 5 is a Likelihood Ratio test of Tobit *vs* Double Hurdle Model. In table 7, LBCpca is the measure of local banking competition constructed by principal component analysis (PCA), and INT is the interaction term between LBCpca and TRANSPpca, the latter being an index of firm transparency constructed by PCA. The variables AGE, TA, TGASS, INCEN, RPI and POP are in natural logarithms. With the exception of HHI, PR, AGE, LBCpca, TRANSpca, SOUTH, POP and the sectoral dummies, all the explanatory variables are lagged one year. The estimated coefficients of the constant term, time and sectoral dummies (ATECO) are not reported. For further description of the variables see Table 2.