BANK SIZE OR DISTANCE: WHAT HAMPERS INNOVATION ADOPTION BY SMES?

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Abstract

A growing body of research is focusing on banking organizational issues, emphasizing the difficulties encountered by hierarchically organized banks in lending to informationally opaque borrowers. While the two extreme cases of hierarchical and non–hierarchical organizations are typically contrasted, what shapes the degree of hierarchy and how to measure it remain fairly vague. In this paper we compare bank size and distance between a bank's branches and headquarter as possible sources of organizational frictions, by studying their impact on small firms' likelihood of introducing innovations. Results show that SMEs located in provinces where the local banking system is functionally distant are less inclined to introduce innovations, while the market share of large banks is only slightly correlated with firms' propensity to innovate.

JEL Codes: G21, G34, O31, R51

Keywords: Functional Distance, Bank Size, Innovation, SMEs.

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1 Introduction

A growing body of research emphasizes the importance of bank organizational form for lending policies[1]. What drives credit allocation, it is typically claimed, is not only the availability of effective information technologies or the possibility of personal face–to–face contacts with borrowers by dislocating branches in the same borrowers' area, but also the organizational complexity of the institution to which the loan office belongs. Put differently, following this line of reasoning, the local branch of a large, nationwide bank competes and allocates resources differently from the branch of a small, local bank.

Underlying this hypothesis are the assumptions that information is widely dispersed and that communicating it within an organization is a costly and imperfect process. A crucial part of information on local borrowers is non–codified and recoverable only by loan officers of local branches with detailed knowledge of the particular environment within which they operate. It is the loan officer who has personal contacts with the borrower, lives in the same community, knows people and firms who do business with the latter, shares a common set of cultural values, social norms and business language. It is their effort at combining hard with soft information on which the ability to select worthy projects depends. However, the amount of resources a loan officer devotes to acquiring soft information is not observable (Milbourn, Shockley and Thakor, 2001; Novaes and Zingales, 2004). Furthermore, soft information available to a loan officer cannot be inexpensively and unambiguously passed on to the upper layers of the parent bank (Garicano, 2000; Stein, 2002; Liberti and Mian, 2006). When banks are hierarchically organized, unobservability of information investments and shortfalls in communication channels within the bank generate incentive problems and agency costs (Berger and Udell, 2002; Stein, 2002; Takáts, 2004), and create an opportunity for influential activities and career concerns (Narayanan, 1985; Hirshleifer and Thakor, 1992; Meyer, Milgrom and Roberts, 1992; Milbourn, Shockley and Thakor, 2001). *Ceteris paribus*, all such matters should produce a sort of liability of hierarchy, with highly hierarchized institutions allocating few resources to activities absorbing a lot of soft information, such as small business lending or innovation financing.

Many authors seem to consider the number of hierarchical levels as the key determinant of organizational frictions and bureaucratization in lending decisions. In this spirit, the great bulk of empirical research has used bank size or structure (being a multi–bank holding organization) to measure the degree of organizational hierarchy, implicitly assuming that as the size or the complexity of a bank increases so does the number of its hierarchical levels (DeYoung, Goldberg and White, 1999; Berger et al., 2005). Laying emphasis on bank size and the number of intra–bank hierarchical levels means conceiving the organizational frictions due to the degree of hierarchy as pertaining to the bank as a whole, even if they affect different types of lending differently.

But this assumption is far from obvious. Recently, a few other studies have suggested that the degree of hierarchy pertains to the specific bank-firm relationship, and not to the bank, as being associated to the location of the lending branch with respect the decisional centres of the bank to which it belongs (Alessandrini, Presbitero and Zazzaro, 2008; Jimenez, Salas and Saurina, 2007). Following these

[1] Theoretically this line of research is well represented by Stein (2002), while for empirical investigations see the studies reviewed below in Section 2.

studies, organizational friction stems from the geographical dispersion of the bank organization by branches and subsidiaries. The conjecture is that incentive problems and the deterioration of soft information in transmission within an organization increase with the "distance" between hierarchical levels (herein, the "functional distance"[2]), rather than with their number. As Klagge and Martin (2005, p. 394–395) suggest:

> A spatially–centralized system, with a single financial centre containing the main financial institutions and capital markets, could result in funds being biased to those firms within close proximity to the centre, relative to more distant firms, given that information on the former is likely to be greater and more reliable than on the latter. Thus firms in the financial core region may have a distinct market advantage compared to firms in financially peripheral regions.

In this case, the testable implication is that the geographical distribution of bank decisional centres is not neutral for the investment decisions of firms[3].

The novel contribution of this paper is to combine functional distance and bank size in the same empirical model. We apply our analysis to a large sample of Italian small and medium enterprises (SMEs), surveyed every three years by an Italian banking group from 1995 to 2003. Since this survey does not contain any information concerning individual loans, we consider the organizational structure of the local banking systems by building aggregate measures of functional distance and bank size at the provincial level. Then we investigate whether the behavior of a firm and its financing constraints are significantly affected by the degree of functional distance of the banking system in the province where it is headquartered and the market share held by big banks in that local market. We first focus on the impact of functional distance and bank size on the firms' likelihood of introducing process and product innovations. If the lower innovative capacity of SMEs located in a province with a highly hierchized banking system were due to a funding gap, we would expect organizational friction of local bank branches to impact relatively more on innovative than on non–innovative SMEs. This is the second hypothesis we investigate, assessing whether the impact of bank organizational friction on the firm's probability of being credit–rationed varies according to the firm's attitude to innovate.

To address possible endogeneity problems, we estimate our empirical models with the instrumental variable methodology. By way of preview, we find that firms located in provinces where the local banking system is functionally distant are less inclined to introduce process and product innovations. Furthermore, in such provinces credit rationing is more likely to occur and innovative firms tend to be penalized. Conversely, we find that the market share of large banks is only rarely statistically significant and when it is, the economic impact on the probability

[2]This terminology was introduced by Alessandrini, Croci and Zazzaro (2005) and re–used by Alessandrini, Presbitero and Zazzaro (2008). Jimenez, Salas and Saurina (2007) instead suggested the alternative label organizational distance.

[3]In the absence of detailed information on the organizational structure of banks, the decisional centre of the bank is typically identified with its headquarter, where lending policies and ultimate decisions on the internal career of loan officers are taken. In this regard, a notable exception is Liberti and Mian (2006) who, however, focus on a case–study concerning a single bank.

of introducing innovation and credit rationing is appreciably smaller than that of functional distance.

The rest of the paper proceeds as follows. Section 2 provides a selective review of the related literature. Section 3 illustrates our data set and the distance variables. Sections 4 and 5 present our empirical exercises, describing for each of them the dependent and control variables, the empirical strategy and the results. Section 6 concludes. Tables and Figures are reported in Annex A and a detailed description of the variables used in the empirical exercises may be found in Annex B

2 Related Literature

2.1 Bank size and lending policies

A large number of studies have analyzed the effect of bank size on credit allocation, loan contract requirements and lending technologies. On the whole, available findings seem to be consistent with the theoretical predictions, suggesting that more hierarchical (i.e., larger) banking institutions find gathering soft information relatively more costly and lending to informationally opaque borrowers less profitable. For example, there is robust evidence for many countries that big banks allocate to small business lending a lower share of their assets, just as there is evidence that large banks involved in consolidation deals reduce loans to small firms[4]. In turn, large and informationally transparent firms appear to be more likely to borrow from large banks (Berger et al., 2005; Uchida, F.Udell and Watanabe, 2007). Others found that the interest rate and collateral requirements of large banks on loans to small firms are lower than those performed by small banks (Berger and Udell, 1996), as are the risk–adjusted earnings (Carter, McNulty and Verbrugge, 2004), suggesting that large banks tend to pick only the best small businesses.

Bank size has also been found to affect the lending technology. For example, there is evidence that large, hierarchical banks rely more on hard information, credit–scoring technologies and impersonal modes of interaction than small banks do (Scott, 2004; Berger and Frame, 2005; Uchida, Udell and Yamori, 2006). Moreover, large banks make less use of exclusive relationships in small business lending and the impact of such relationships on credit terms is greater when small firms borrow from weakly hierarchical banks (Angelini, Di Salvo and Ferri, 1998; Cole, Goldberg and White, 2004; Kano et al., 2006; Uchida, F.Udell and Watanabe, 2007). Interestingly, many of the competitive advantages of large banks in using transactional lending technologies seem to hold more strictly once one has controlled for endogeneity problems due to borrower preferences for such technologies (Berger et al., 2005).

The difficulties of small firms in borrowing from large banks are, however, only partially confirmed by studies conducted at the market level. For example, Craig and Hardee (2007) found that, in the U.S. banking industry, firms located in markets where the share of deposits controlled by large banks is higher are less likely to use bank debt. By contrast, Jayaratne and Wolken (1999) suggested that for small firms the probability of having a credit line and using trade credit is not significantly

[4] For the US banking industry, see Berger and Udell (1996); Peek and Rosengren (1998); Strahan and Weston (1998). For the Italian banking industry, see Sapienza (2002); Alessandrini, Calcagnini and Zazzaro (2008). For Belgium, see Degryse, Masschelein and Mitchell (2005).

affected by the presence of small banks in the market. In the same vein, Berger, Rosen and Udell (2007) found that small firms face a higher probability of having a credit line from a large bank as long as the share of large banks in the local market increases, suggesting that small firms are not penalized by large banks. Working on Italian data, Bonaccorsi di Patti and Gobbi (2001) found that the share of branches held by small banks in Italian provinces does not have a differential effect on loans to large and small firms.

2.2 Functional distance and lending policies

The empirical literature offers various, consistent clues of the importance of agency and communication costs in geographically dispersed bank organizations. A number of studies, for example, have provided evidence that loan officers are usually asked to rotate within a multinational bank frequently (Hertzberg, Liberti and Paravisini, 2008) and the average time spent by a loan officer of nationwide banks in a specific branch is significantly lower than in local banks (Ferri, 1997). Moreover, empowering loan officers increases the effort they devote to screening and monitoring borrowers, and improves the performance of the bank (Liberti, 2003), but also increases the resources that the parent bank devotes to loan reviewing activities (Udell, 1989).

The liability of geographical dispersion has also found indirect confirmation in the effects it has on bank market value and cross-border M&As. For example, Klein and Saidenberg (2005) found that the market–to–book equity ratio of bank holding decreases with the number of chartered bank subsidiaries. In a similar vein, there is broad evidence that geographic diversifying M&As are not value enhancing for dealing banks (DeLong, 2001; Amihud, DeLong and Saunders, 2002; Vennet, 1996; Beitel, Schiereck and Wahrenburg, 2004), and that geographical and cultural distance hinders international banking consolidation (Buch and DeLong, 2004).

Next, there is robust evidence concerning different countries at different levels of financial and economic development that distance–related organizational frictions affect bank lending policies and credit allocation by local managers. A first strand of studies which contrasts foreign and out–of–market owned banks with domestic and in–market owned banks shows that the former have a disadvantage in small business lending and allocate fewer resources to this activity than the latter (Keeton, 1995; Cole, Goldberg and White, 2004; Carter, McNulty and Verbrugge, 2004; Alessandrini, Croci and Zazzaro, 2005; Carter and McNulty, 2005).

Similar findings have been obtained by a second strand of recent studies that introduced more accurate measures of functional distance. Alessandrini, Presbitero and Zazzaro (2008) found that small Italian firms are more likely to be credit rationed if they are located in provinces where a greater percentage of branches belong to banks headquartered in physically distant provinces and in provinces with different social and economic environments. Also, Alessandrini, Calcagnini and Zazzaro (2008) found that in Italian bank acquisitions, the greater the cultural distance between the provinces where the dealing partners are headquartered, the greater are the changes in acquired banks' asset allocation in favour of large borrowers and transaction-based financial activities, at the expense of small, opaque borrowers.

Consistent with the hypothesis that functionally distant banks specialize in lending to more transparent and safer borrowers, but by using loan–level data, Mistrulli and Casolaro (2008) found that in Italy functionally distant banks tend to operate with safer borrowers who they can charge low interest rates. Similarly, Jimenez, Salas and Saurina (2007) showed that, for Spanish banks, the likelihood of the usage of collateral decreases with the distance between the province where the bank is headquartered and the province of the borrower, irrespective of the level of experience accumulated by the bank in the local market. Moreover, the effect of functional distance on credit allocation seems to vary with the ownership form of the bank with savings banks that specialize more in lending to distant small businesses relative to commercial banks (Delgado, Salas and Saurina, 2007).

With regard to the U.S., Berger and DeYoung (2006) found that cost and profit efficiency of affiliated banks in U.S. multibank holdings are negatively correlated with the kilometric distance from the parent bank, suggesting that geographic dispersion reduces the capacity of the bank holding to keep under control the resource allocation of each component of the bank group and entails heavy agency costs in terms of non-optimal input and asset allocation.

Finally, two interesting attempts to evaluate the relative importance of bank size and distance as a source of organizational problems of efficiency control and communication were provided by Mian (2006) and Liberti and Mian (2006). Using loan-level data from Pakistan, Mian (2006) found that the degree of engagement in relational contracts and lending to informationally opaque firms is greatest for branches of domestic banks, next greatest for branches of Asian banks and least for branches of non–Asian foreign banks. By contrast, he could find no significant effect of bank size on credit allocation and relational lending. Liberti and Mian (2006) analyzed a large multinational bank operating in Argentina and documented that the sensitivity of the amount of credit facility granted to soft (hard) information decreases (increases) with the hierarchical level at which the credit line is approved. At a first glance, this result is consistent with the idea that what drives communication friction is the number of hierarchical levels. However, the authors also found that the decline in soft information sensitivity is not gradual over hierarchical levels, but takes place just in between levels where the officer who approves the loan sits in a different location from that of the previous level officer, suggesting that what really matters is the functional distance between hierarchical levels.

2.3 Banks and innovation

The third strand of literature with which our paper is clearly related is that on financial impediments to innovation adoption faced by firms. A number of recent studies have addressed this question by using the first, second and third "Community Innovation Survey" carried out by the European Union and Eurostat on firms in EU area countries. From these studies it emerges that the lack of appropriate sources of finance is one of the main obstacles both to the probability of innovating and the intensity of innovating all through the Europe (Stoneman and Canepa, 2002; Mohnen and Roller, 2005; Savignac, 2006; Mohnen et al., 2008)[5]. Moreover, insufficient finance shows a high degree of complementarity with other hampering factors like the perceived risk by firms, innovation costs (Galia and Legros, 2004) or insufficient skilled personnel, lack of cooperation with other firms and regulatory obstacles (Mohnen and Roller, 2005).

[5]Similarly, using a different survey for the UK, Stoneman and Canepa (2003) show the adoption times of new process technologies are significantly sensitive to firm's cash flow

Most closely related to our analysis, three recent studies by Benfratello, Schiantarelli and Sembenelli (2008); Ferri and Rotondi (2006), and Herrera and Minetti (2007) investigated the effect of local banking development and relationship lending on the adoption of innovation by Italian manufacturing firms, extracting firm level information from the same source (i.e., the three-yearly Unicredit survey on Italian manufacturing firms) that we use in the empirical exercises below. Benfratello, Schiantarelli and Sembenelli (2008) found that the probability of introducing an innovation is significantly higher for firms headquartered in provinces where the proportion of bank branches with respect to population is higher. This positive effect of branch density proves to be more robust for process than for product innovation and greater for small and high–tech firms. Moreover, it maintains its statistical significance once endogeneity problems are addressed by using instrumental variable estimations.

Herrera and Minetti (2007) concentrated their analyzes only on the 8th wave of the Unicredit survey covering the period 1998–2000. They documented that, once instrumented, the number of years by which a firm mantains a customer relationship with its main bank is positively correlated with the probability of introducing innovation. Unlike Benfratello, Schiantarelli and Sembenelli (2008), Herrera and Minetti found that it is the likelihood of product innovation which is more sensitive to relationship banking. Moreover, they found that branch density and other measures of local banking development are no more statistically significant.

Ferri and Rotondi (2006) extended the study by Herrera and Minetti by adding data from the most recent Capitalia survey (covering the period 2001–2003), augmenting the model with other control variables and distinguishing industrial district and non–industrial district firms. On the whole, their findings confirmed results obtained by Herrera and Minetti (2007), suggesting in addition that the duration of the bank relationship also strongly affects the likelihood of process innovation.

3 Variables and descriptive statistics

3.1 Data sources

We construct a large dataset consisting of micro–data on Italian manufacturing SMEs and macro–indicators of banking development and organizational structure for the 95 Italian provinces[6].

Information on innovation adoption, credit rationing and other firms' characteristics are drawn from the widely used Survey of Manufacturing Firms published every three years by the Italian banking group Unicredit (and formerly by Mediocredito Centrale and Capitalia). The survey collects a large set of information on a representative sample of Italian SMEs with 11–500 employees — stratified by five firm size classes, four Pavitt's industrial sectors, and firm location between the North of Italy and other regions —, and the universe of firms with more than 500 employees. Attached to the survey are also balance sheet data covering the entire survey period.

In this paper, we merge the last three waves of the survey covering the periods 1995–1997, 1998–2000 and 2001–2003. The pooling sample has information on

[6]Italy is currently divided into 107 provinces, which are grouped into 20 administrative regions. However, since some provinces were recently constituted, we use the old classification of 95 provinces.

13,327 firms. Since our empirical exercises focused on SMEs, the sample size was reduced to 12,872 observations. Finally, due to missing data, misreporting and a trimming procedure that excludes extreme values of all firm-level variables, we are left with a number of observations ranging from 6,919 to 7,603 depending on the estimated models.

Data on the location of bank headquarters, bank holding composition and the provincial distribution of branches by banks come from the Bank of Italy, for the sample period as well as for 1936 and 1971. These two years will serve as benchmarks to build instruments for our instrumental variable estimation (see below, section 4.1). Information on the asset size of banks was taken from Bilbank, a data set produced by the Italian Association of Bankers (ABI) collecting balance-sheets of Italian banks. Finally, data on population and real value added at the provincial level are taken from the National Institute of Statistics (ISTAT).

3.2 Innovation variables

Our endogenous variables are self-reporting responses to survey questions concerning the adoption of innovation and credit rationing. Specifically, the question on innovation is the following: *"During the three survey years, did the firm make any product and/or process innovations?"*. Starting from this question we build three dummy variables: (1) INN, which is equal to 1 if the firm adopted a product and/or a process innovation and 0 otherwise, (2) $PROCESS$, which is equal to 1 if the firm introduced a new technology and 0 otherwise, and (3) $PRODUCT$, which is equal to 1 if the firm introduced a new product and 0 otherwise.

The second survey question is on credit rationing. In this case, the survey asked firms, *"In the last year of the survey would the firm have wanted more credit at the interest rate agreed with the bank?"*. We then build a dummy variable RAT, which is equal to 1 if the firm answered yes and 0 otherwise. It is worth noting that the survey question that we use to classify a firm as rationed does not allow us to distinguish quantity from price rationing. Although the survey asked firms more detailed questions to disentangle the type of rationing, we choose to use the more general question on rationing because we are interested in financing constraints to innovation and not in the existence of quantity constraints *per se*[7].

As shown in Table 1, 50% of the firms in our sample stated they had adopted process innovation, while product innovation was adopted by only 28% of firms. In both cases, the likelihood of introducing innovations increases with firm size and is higher for firms that make investments in R&D (Table 2). With regard to the RAT variable, 15% of firms stated they were rationed by banks; the percentage decreases with firm size and, for small firms, is higher for those which claimed to adopt innovations.

3.3 Organizational diseconomies of local banking systems

As we stated above, we distinguish two sources of organizational diseconomies within a bank: the number of hierarchical levels, that we proxy with bank size,

[7] Furthermore, (a) the order in which the other questions appeared in the survey changes with the waves and therefore responses are not perfectly comparable across the three data sets; (b) the number of missing data is much higher.

and the functional distance between hierarchical levels, that we proxy with the kilometric distance between the head office of the parent bank and its own branches.

We build the organizational variables at the provincial level as the functional distance and the size structure of the local banking system. Since in Italy more than 90 percent of credit to borrowers located in a province is granted by branches located in the same province, we can confidently assume that in each province the great bulk of local SMEs borrow from the local banking system.

Functional distance is computed as the number of branches operating in a province j, each weighted by the logarithm of one plus the kilometric distance between the capital of that province and the capitals of provinces where parent banks are headquartered[8]:

$$FD\_KM_j = \frac{\sum_{b=1}^{B_j} [Branches_b \times \ln(1 + KM_{j,z_b})]}{\sum_{b=1}^{B_j} Branches_b} \quad (1)$$

where B_j is the number of banks operating in the province j, $Branches_b$ is the number of branches belonging to the bank b, and z_b is the province where the headquarter of the bank b is located.

The size structure of the local banking system is computed by the ratio of branches owned by large banks to the total number of branches operating in each province (Sh_LB)[9]. A bank is classified as large if it has total assets of at least 50 million euros computed at 2003 prices[10].

For affiliated banks we assume that the ultimate control of local branches is in the hands of the parent bank of the holding company, so that the headquarter location and the size are those of the holding company. Actually, our data do not allow us to disentangle how much decisional autonomy a chartered bank loses when it enters a banking group. For robustness, we calculated the organizational structure indicators under the alternative assumption that the ultimate control on lending decisions is taken by the chartered bank obtaining very similar estimation results[11].

Summary statistics of organizational variables for the pooled sample are reported in Table 1. Although the two indicators are positively correlated (Table 3), they follow a different pattern during the sample period. As shown in the left-hand panel of Figure 1, FD_KM and Sh_LB exhibit a sharp increase from 1995 to 2003, as a result of the intense process of mergers and acquisitions that affected the Italian credit markets at the time. On average, the share of large banks in Italian provinces was 31% in 1995, increasing to 48% in 2003. The increase in functional distance was on average more limited (less than 30%). At the same time, the right–hand panel of Figure 1 reveals that the variability of Sh_LB across provinces, measured

[8]Kilometric distances are calculated with a Jenness (2005) extension of the ArcView GIS software. In a previous study on firms' financial constraints, we also use a weighting rule based on cultural and economic distance, captured, respectively, by the social capital and a dissimilarity index of the economic structure of the two provinces (Alessandrini, Presbitero and Zazzaro, 2008). Since kilometric, cultural and economic functional distance indicators have proved to give very similar results, for the sake of space, here we focus only on the kilometric weighting rule.

[9]This indicator was recently used by Berger, Rosen and Udell (2007) and Delgado, Salas and Saurina (2007).

[10]Econometric findings are robust to a change in the size threshold at 25 million euros. Results are available on request.

[11]For the sake of space we do not report tables for these results, but they are are available on request.

by the coefficient of variation, experienced a marked reduction over the considered span of time, while the geographical dispersion of functional distance decreased at a much slower pace.

3.4 Local banking development and firm–specific explanatory variables

In our regression we control for the degree of development of the local banking system and a number of firm characteristics.

With regard to the former, we consider the operational proximity of the local banking system and the degree of market concentration. The operational proximity ($BRANCHES$) is measured by the ratio of the number of bank branches working in a province to the resident population. This indicator is widely used in the banking literature and has been recently employed by studies on financial constrains to firms' innovation adoption (see Section 2.3). The degree of concentration of the local credit market is measured by the Herfindahl–Hirschman Index (HHI), computed on the share of branches held by banks operating in a province.

As firm characteristics we consider size, financial structure, export and innovation vocation. More specifically, the size of firms is measured in terms of employee numbers ($WORKERS$). To allow for possible non–linearities, we construct five dummy variables for the classes of employees 11–20, 21–50, 51–100, 101–250 and 251-500, where the first class is taken as the baseline in the econometric exercises. The firms' financial structure is captured by return on investment (ROI), the degree of leverage ($DEBT$) and the number of banks from which each firm borrows (ML). The vocation to export is proxied by an indicator variable that has a value of 1 for firms exporting a share of their sales and 0 otherwise ($EXPORT$). Finally, the propensity to innovate is captured by two different measures: (1) the ratio of R&D expenditures to the stock of capital (RDK), and (2) the share of sales coming from innovative products ($INNOVATION$)[12].

4 Innovation Adoption

4.1 Methodology

The basic question we address in this paper is: "Does the degree of organizational friction in the local banking system hamper the adoption of process and product innovation by local SMEs?" More specifically: "Does the number of and/or the distance between hierarchical levels of banks working in a province adversely affect the likelihood of local firms to introduce innovations?"

To answer this question we estimate two econometric models. First, we estimate a pooled probit model:

$$Pr(I_{ijt}) = \Phi(FD\_KM_{jt}, Sh_L B_{jt}, BANKING\text{–}DEV_{jt}, FIRM_{it}, D_j, D_t) \qquad (2)$$

where Φ is the normal distribution function. The dependent variable is, alternatively, the probability of a firm i located in a province j during the survey pe-

[12] A detailed description of these and all other variables used in the empirical analysis is reported in B.

riod j introducing (i) innovations *tout court* (INN), (ii) new process technologies ($PROCESS$); (iii) new products ($PRODUCT$). $BANKING\text{–}DEV_{jt}$ includes $BRANCHES$ and HHI, while $FIRM_i$ includes ROI, RDK, $EXPORT$ and $WORKERS$. Furthermore, we also include dummy variables for industries, regions (D_j) and waves (D_t)[13].

We chose not to exploit the time dimension of data due to the way the survey's sample is built. Each Unicredit survey wave has a rotating panel consisting of one third of firms interviewed in the previous wave. Therefore, an unbalanced panel would include a very large number of groups (i.e., of firms present in only one of the three waves) drastically reducing the degree of freedom of fixed effect estimations, while a balanced panel built on three waves would include only one tenth of the original observations. Moreover, panel members with specific characteristics opt out of the panel in a non–random fashion, so introducing a high degree of panel attrition and bias in the estimates that could well outweigh the efficiency gains of exploiting unobserved firm–specific heterogeneity (Nese and O'Higgins, 2007).

As is typical of any analysis of the relationship between the real and financial sphere of the economy, equation 2 could suffer from reverse causality and omitted variable problems. First, organizational and banking development variables could be endogenous to innovation propensity of local firms. More innovative firms will grow more, fostering local development and promoting the opening of new branches and the acquisition of local banks. Second, it is possible that both the structure of a local banking system and the innovation decisions by local firms are jointly driven by other unobserved factors.

To address these problems we follow a instrumental variable (IV) two–stage procedure proposed by Rivers and Vuong (1988) and implemented by the Stata command IVPROBIT. In the first stage, we run OLS regressions of FD_KM, Sh_LB, $BRANCHES$ and HHI on all covariates included in the structural equation 2 plus some variables that are likely to be correlated with our endogenous variables, but not with the decision to introduce new technologies and products. Second, we include the fitted values and the estimated residuals of the first–step probit regressions into the equation (2)[14]. This two–stage procedure has the advantage of providing a simple test of the exogeneity of FD_KM, Sh_LB, $BRANCHES$ and HHI. Specifically, the Conditional Likelihood Ratio (CLR) is run adding the residuals from the first–stage OLS regressions in the probit model and testing their joint significance (Wooldridge, 2002).

With regard to the choice of instruments, we follow Guiso, Sapienza and Zingales (2004) and, as is now standard in the empirical literature on Italy,[15] we assume the structure of the Italian banking system at 1936 and 1971 as the true exogenous factor. The geographical distribution of banks and branches in 1936 came about as a response of the regulatory authority to the 1930–1931 banking crisis and did not follow the strict logic of profit.

[13]For industry dummies we follow the Ateco two–digit classification for economic activities provided by the National Institute of Statistics and based on the international classification NACE rev.1.

[14]As acknowledged by Wooldridge (2002), the two–stage procedure is less efficient than the Maximum Likelihood estimator and does not directly estimate the coefficients of interest but the scaled coefficients. However, it has significant computational advantages, especially when the estimated model includes more than one endogenous variable in which case the MLE generally does not converge.

[15]See, Herrera and Minetti (2007); Ferri and Rotondi (2006); Benfratello, Schiantarelli and Sembenelli (2008); Alessandrini, Presbitero and Zazzaro (2008) and Guiso, Sapienza and Zingales (2007).

> The financial system which Beneduce and Menichella in 1933 had to create from the ruins of the previous system – Ciocca (2001, p. 41, our translation) writes – remained unchanged and basically accepted until wage and oil stagflation in the 1970s. Today this system no longer exists.

Consistently, Guiso, Sapienza and Zingales (2004) show that the number of branches per person and its distribution by size in 1936 were unrelated to the regional economic development of the time and can therefore be considered strictly exogenous with respect to innovation decisions in subsequent years. Moreover, the geographical distribution of branches in 1936 is significantly correlated with the local banking development in the 1990s.

In this spirit, we construct five instrumental variables at the provincial level: (1) the number of branches per 10,000 inhabitants in 1936 ($BRANCHES36$); (2) the share of branches owned by large banks in 1936 (Sh_LB36)[16], (3) the share of branches owned by credit cooperative banks in 1936 ($CCB36$); (4) the share of branches owned by saving banks in 1936 ($SB36$); (5) the functional distance of local banking systems calculated with respect to the geographical distribution of branches in 1971 (FD_KM71)[17]. Apart from $CCB36$, the other instruments appear to be significantly correlated with the average values of FD_KM, Sh_LB and $BRANCHES$ variables over our sample period (Table 3).

The second econometric model we use to estimate the propensity to innovate of SMEs is the ordered probit. In this case, we assume that the alternative decisions of not introducing innovation, adopting either process or product innovations and adopting both stem from a unique choice model, and are driven by the same latent variables. In other words, we construct a discrete variable $INN3$ whose value depends on the "propensity to innovate". More specifically, $INN3$ is equal to 0 when the firm reports no innovation adoption, to 1 when it has adopted a process or a product innovation, and assumes value 2 when both types of innovations have been introduced. Then we estimate the impact of our organizational, banking development and firm-specific variables on the probability of these three events.

4.2 Results

4.2.1 The innovation choice

In Table 5 we report the estimation results of equation (2) concerning the likelihood of SMEs introducing innovations (INN). The standard probit regression coefficients from the basic model are reported in column (1), while column (2) shows the IV results. Columns (3) and (4) display IV estimations of a second model augmented by an interaction term between FD_KM and Sh_LB, respectively, and R&D expenditures to take into account possible heterogeneous effects of banks' organizational diseconomies on firms' propensity to innovate. At the bottom of the Table we report, amongst different diagnostics, the CLR test. For the basic specification of the innovation adoption model, the CLR test fails to reject the null of exogeneity. Nevertheless, the residuals from the auxiliary OLS regressions of

[16] Since data on bank branches in 1936 are classified by bank institutional type, we consider the "Istituti di Credito di Diritto Pubblico" and the "Banche di Interesse Nazionale" to be large banks.

[17] The choice of 1971 was dictated by the fact that data on the branch distribution by bank were not published before this year. However, since the structure of the Italian banking system remained virtually unaltered until the end of the 1970s, we take the FD indicator at 1971 as a valid instrument.

FD_KM and HHI prove to be significant, suggesting their endogeneity (Table 4, column 5). Moreover, in the augmented model the p–value of the CLR test is below the 5 percent level of significance, as well as when we look at process and product innovation models (Table 6). All in all, these results indicate that the standard probit estimator can be biased and non–consistent, and recommend the use of IV estimation techniques.

Furthermore, first–stage regressions and the Sargan test corroborate the validity of employed instruments. As shown in Table 4, instruments are significantly correlated with the endogenous variable and the F–test always strongly rejects the null of them being jointly not significant. The Sargan overidentification test, reported in Table 5, does not reject the hypothesis that the excluded instruments are uncorrelated with the error term of the structural equation.

Looking first at the key indicators of organizational diseconomies, the result that clearly emerges is that FD_KM, once instrumented, reduces the probability of SMEs introducing innovations, while the market share of large banks (Sh_LB) has no significant effect. This finding is confirmed in all the three IV specifications reported in Table 5. However, as shown in columns (3), the adverse effect of functional distance is lower for firms that invest greater resources in R&D. In particular, the coefficient on FD_KM is equal to -0.269 for SMEs not investing in R&D (column (2)), while it decreases to -0.202 for a firm with an average RDK ratio and to -0.082 for firms at the 90^{th} percentile of the RDK distribution. As firms investing in R&D are usually larger (Table 2) and properly organized, this mitigating effect of RDK corroborates the idea that distance of loan offices from decisional centers is especially harmful for firms unable to provide banks with standardized and reliable hard data. The effect of Sh_LB, instead, remains statistically non–significant regardless of the firm's attitude to invest in R&D.

To assess the importance that local banking organizational frictions have for the probability of adopting an innovation, we calculate the impact that a change from the first to the third quartile of FD_KM and Sh_LB distributions have on the predicted propensity to innovate by each firm and average it across the sample. We investigate two aspects concerning the differentiated effect of FD_KM and Sh_LB on innovation relative to: 1) the size of the firms, 2) their capacity to invest in R&D.

Figure 2 provides visual confirmation that functional distance is the main channel through which organizational diseconomies impact on innovation adoption by SMEs. Increasing FD_KM from the first to the third quartile of its distribution[18] leads to a remarkable drop in the predicted probability of introducing innovation. This effect is stronger as the firm size becomes smaller, producing a reduction of more than 15% for firms with 11–20 employees. As stated above, the negative impact of functional distance on the attitude to innovate is lower for firms investing in R&D and the difference in firms that do not carry out R&D is more apparent for those of average size (51–100 employees). Summarizing, the firms which are most penalized in their innovation effort by the functional distance of the local banking system are the smaller firms not investing in R&D, whose predicted probability of adopting innovations decreases from 52% (first quartile of FD_KM distribution) to 37% (third quartile).

[18] To illustrate, the change in FD_KM from the first to the third quartile is similar to the evolution actually experienced by FD_KM between 1995 and 2003 in the province of Parma, and it is also similar to the difference in 2003 between Brescia (first quartile) and Parma (third quartile) in 2003.

Moving on to the other credit market indicators, we find that small and medium enterprises located in more concentrated credit markets have a higher probability of introducing innovation. Such a positive correlation between INN and HHI appears to be much stronger in IV estimates and it is consistent with the hypothesis that less banking competition stimulates relation–based lending and facilitates the funding of opaque borrowers/projects (Petersen and Rajan, 1995; Cetorelli, 1999). The number of branches per inhabitant, $BRANCHES$, proves non–significant. This result is contrary to the evidence provided by Benfratello, Schiantarelli and Sembenelli (2008), but consistent with the findings reported in Ferri and Rotondi (2006) and Herrera and Minetti (2007), and might be due to the fact that we control for other banking development variables.

Finally, coefficients of firm–specific control variables are significant, stable in modulus and with the expected signs irrespective of the estimation method. In particular, more profitable firms, as well as those that invest more heavily in R&D and export part of their production abroad are more likely to adopt innovations. Moreover, the probability of introducing an innovation steadily increases with the size of the firm. The F–test on the joint significance of both regional and industry dummies suggests the presence of significant geographical and sectoral differences in innovation propensity, related to region– and industry–specific fixed effects.

4.2.2 Types of innovation and propensity to innovate

In this Section we consider the type of innovation firms introduce by distinguishing process and product innovations. First, we analyze separately the decisions to adopt a new technology and a new product. In principle, it is ambiguous which type of innovation should be more damaged by bank organizational diseconomies. On the one hand, by reducing loans to innovation projects, hierarchical banks would be especially detrimental to process innovation which entails new machinery requiring lumpy investments and a great amount of (external) finance. On the other hand, by shying away from relation–based lending, hierarchical banks would discourage the innovative vein of their clients, thereby hindering the introduction of product improvements.

In order to save space, in Table 6 we report only results for the IV estimates, which the standard diagnostic displayed at the bottom of the table suggests adopting[19]. Interestingly, we obtain evidence of a differentiated effect of the distance and number of hierarchical levels on the type of innovation introduced by firms. Once instrumented, the coefficient of FD_KM is negative for both process and product innovations, but it is statistically significant only for the former. By contrast, the market share of large banks is negatively associated with the probability of introducing product innovations[20], while it has no effect on the likelihood of adopting process innovations, consistent with the aversion of large banks to relation-based activities.

When we discriminate the impact of the organizational variable for the degree of firm engagement in R&D, only the interaction term between functional distance and RDK for product innovation is significant, and with a positive sign (column 4). Moreover, allowing for the heterogeneous effect of functional distance according to firm's R&D expenditures makes FD_KM a significant determinant also for

[19]The probit estimates are available upon request.

[20]In the standard probit model the coefficient on Sh_LB is not significant.

product innovations and with an economic impact much greater than Sh_LB. The market share of large banks further decreases the probability of introducing product innovation, but without any differentiated effect related to the firm's engagement in R&D, while it has no effect on the likelihood of adopting process innovation.

Finally, in Table 7 we report the results of the ordered probit model concerning the strength of the firms' innovative vein. In this case, since we do not employ instrumental variable techniques, we are able to report marginal effects for the explanatory variables calculated at their sample means.

On the whole, the results confirm those discussed above. Control variables are still significant, with RDK and firm size being the variables with the greatest marginal effects. This is especially true for the two extreme categories of $WORKERS$: as regards the smallest class of businesses, having more than 250 employees raises the probability of adopting innovation by 16%, while it reduces the likelihood of not innovating at all by 17.4%.

As regards the market–level variables, the degree of concentration is still significant with a positive effect on fostering the adoption of innovations, while $BRANCHES$ has no significant impact. Moving on to the organizational variables, once again the estimates suggest that only functional distance impacts on the probability to introduce innovation, while the share of large banks is not statistically influential. The marginal effect of FD_KM for the average firm is almost twice as great for the likelihood to introduce product and process innovations together than for one of them taken singularly. The effect of organizational frictions arising from distance is considerably reduced for firms investing in R&D: the marginal effect of FD_KM on the probability of introducing product and process innovation decreases from -0.010 ($RDK = 0$) to -0.007 for a firm with an average level RDK intensity and to almost zero for a firm at the 90^{th} percentile of RDK distribution. Similar results hold for the probability of introducing only one type of innovation.

5 Credit Rationing

5.1 Methodology

The negative impact of bank organizational frictions on the probability of adopting an innovation might be due to the greater financial constraints levied by hierarchical banks on firms that wish to introduce innovations, but it also might be the consequence of the failure of functionally distant, large banks to encourage their small borrowers to innovate and grow. To disentangle these two channels of influence, we estimate a probit model for the probability of firms being credit–rationed for the whole sample and discriminating between innovative and non–innovative firms on the ground of the INN dichotomous variable.

If banks' organizational frictions affect innovation by making access to credit harder, innovative firms in provinces where the local banking system is more hierarchical should be relatively more credit–rationed than innovative firms in other provinces (i.e., the estimated coefficients on FD_KM and Sh_LB should be larger for the innovative firms). Otherwise, the negative impact of the organizational frictions of the local banking system on firms' innovation propensity found in the previous Section would act on a more general level by reducing the ability of firms to see innovation opportunity and assess its economic benefits.

Apart from the local banking system and firm characteristics described in the previous section, in this model we further control the degree of leverage ($DEBT$) and multiple lending relationships (ML). Dummy variables for industries, macro–regions and waves are also included[21].

Once again, to address endogeneity and omitted variable problems we run IV estimations, by instrumenting banking variables with the same instruments described above in Section 4.1.

5.2 Results

Table 8 reports the estimation results. As for Table 5, column (1) of Table 8 shows the standard probit results, while the remaining columns focus on the instrumental variable ones. With respect to the latter, the first stage estimates, the CLR and the Sargan test suggest that the banking variables are endogenous and the instrument set is valid, except for the sub–sample of non–innovative firms, for which the CLR test fails to reject the null hypothesis of exogeneity (column (3))[22].

Control variables are generally statistically significant and with the expected signs. Firm size is negatively associated with the probability of credit rationing, even if this relationship does not appear to be strictly linear: firms employing from 50 to 250 workers are not significantly less rationed than the smallest firms with less than 20 workers, taken as the reference category, while for the other firms the greater the size class to which they belong, the lower is the probability of being rationed. We then find evidence that less indebted and more profitable SMEs are less credit–rationed, while a multiple lending relationship (ML) does not have a very significant effect on the probability of rationing. Finally, more innovative firms are, other things equal, more likely to have their credit applications denied, consistent with their being more informationally opaque and perceived as riskier by banks.

As regards the structural characteristics of local credit markets, once again the IV results suggest a beneficial effect of the Herfindhal index on SMEs, it being negatively associated with the likelihood of credit rationing. The number of branches per capita is found to soften firms' financing constraints only in probit estimates, while its coefficient becomes not statistically significant once we correct for the endogeneity bias.

Moving on to the organizational variables, the evidence provided after instrumenting the banking variables shows that both the functional distance of the local banking system and the market share of large banks make financing constraints to SMEs more binding (column (2)). However, the former has a higher effect on credit availability to local firms. In fact, compared to a likelihood of being credit rationed for the average firm equal to 15 per cent, a firm located in a province at the third quartile of the FD_KM distribution faces a probability of credit rationing of 21.6 per cent, while being located in a province at the first quartile reduces this probability to 4.7 per cent. On the other hand, the variability induced by a similar

[21] Because of the reduced sample size in the sub–sample estimates, we include five dummies for the Italian macro–regions (North–East, North–West, Centre, South, Islands) and 13 industry dummies instead of the regional and two–digit Ateco classification. Thus, we avoid dropping from the regression a number of observations which perfectly predicts RAT

[22] To save on the number of tables, we omit first–stage regressions, which show a high degree of correlation between instrumented and instrumental variables.

change in Sh_LB is smaller. Moving to a province where the market share of large banks is around one third (first quartile of the Sh_LB distribution) reduces the probability of rationing to 8.1 per cent, while operating in a province where large banks constitute half of the local market raises that probability to 18 per cent.

In columns (3) and (4) we discriminate between firms which have or have not introduced product and/or process innovations. The results show that functional organizational frictions represent a constraint exclusively for firms that adopted innovations, supporting the hypothesis that distance between hierarchical levels creates a funding gap to innovative SMEs. By contrast, the market share held by large banks in the province does not have any clear differentiated effect on innovative and non–innovative firms. Finally, innovative firms benefit from more concentrated markets. Since information asymmetries are particularly relevant for innovative projects, a higher degree of market concentration could promote the development of strong banking ties to overcome information asymmetries. These result holds even when controlling for the share of sales coming from innovative products ($INNOVATION$), whose autonomous effect on $Pr(RAT)$ is generally significant.

6 Conclusions

A crucial issue left largely unexplored by the recent literature on hierarchical banks is the basic source of organizational frictions driving the difficulties in information–intensive lending or, put differently, how to measure the degree of hierarchy. Some authors emphasize the size of the bank, implicitly suggesting that the degree of hierarchy pertains to the bank as a whole, depending on the number of intrabank hierarchical levels (Stein, 2002; Berger et al., 2005; Degryse, Laeven and Ongena, 2006). Others, instead, stress the role of the distance between the local branch, where information on borrowers is collected, and the bank's headquarters, where the decision–making authority is located (Alessandrini, Presbitero and Zazzaro, 2008; Jimenez, Salas and Saurina, 2007). In this case, the degree of hierarchy pertains to the specific bank–firm relationship, in that it depends on the location of the lending branch.

In this paper, we conducted our analysis at the aggregate level. We contrasted the effect of bank size and bank–branch distance on innovation adoption by SMEs by constructing two indicators of the degree hierarchy of a local (provincial) banking system, functional distance and size structure. Our results show that the distance between bank decisional centres is the main organizational feature accountable for the negative impact of hierarchy on innovation financing. More specifically, the functional distance of the local banking system is significantly and negatively associated with the likelihood of local SMEs introducing innovations. This adverse effect operates through the tighter financing constraints that innovative firms experience in provinces with a functionally distant banking system. The hindering effect of the size structure of the local banking system on innovation adoption is much weaker and restricted to product innovations.

In closing, our findings convey two main policy–oriented messages. First, at the aggregate level, they advise against blanket, undifferentiated policies promoting bank consolidation, while they are sympathetic with "regional champion" policies. A thoughtful appraisal of the consolidation trend in banking occurred in the last two decades and of the expected coming wave of cross–border M&As should balance the benefits of having more efficient, competitive and globalized banks with the costs of organizational diseconomies due to the centralization of bank headquarters (Klagge and Martin, 2005). The risk of this change in the spatial organization of banking industry is the marginalization of small local borrowers, the restraint in innovation diffusion and the decline in the economic and financial power of peripheral regions [23]. Therefore, the competitiveness of a region depends on policies aimed at promoting services' supply and network externalities in order to preserve and attract bank headquarters (Henderson and Ono, 2005; Strauss-Kahn and Vives, 2005; Bel and Fageda, 2008). The presence of a strong local bank competitor seems to be critical for sustaining innovative efforts of local SMEs, for lending to informationally opaque borrowers and, more generally, for focusing banking competition on the needs of local economic development. In addition, to contrast the inescapable increasing spatial concentration of bank decisional centers in the global banking era, it appears urgent to design policies supporting the development of other sources of soft–information–based external financing like venture capitalists, business angels and financial incubators, complementing the lending activity of banks towards innovative SMEs (Klagge and Martin, 2005).

The second policy indication is at the bank level. The negative impact of banking hierarchy on soft information firms/projects can be reduced by a more decentralized organization, adapting to the different needs of firms operating in different local systems. Such a flexible approach in bank organization would provide advantages to innovative SMEs, penalized in their financial needs when examined by distant bank centers. What is required is a change in emphasis in bank organization from the search for economies of scale by using standardized, arm's–length lending technologies, to economies of scope by making specialized credit instruments available to the more dynamic innovative SMEs. Once again, therefore, it is not a matter of bank size, but rather of bank strategy and organizational structures.

[23] Holloway and Wheeler (1991); Meijer (1993); Pike (2006); Bel and Fageda (2008).

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A Tables and Figures

Table 1: Variables: Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
		Dependent variables			
INN	7,205	0.587	0.492	0	1
$PRODUCT$	7,205	0.279	0.449	0	1
$PROCESS$	7,633	0.504	0.500	0	1
RAT	7,633	0.149	0.356	0	1
		Credit market variables			
FD_KM	7,633	3.389	1.022	0.707291	6.497411
(in years)	7,633	148.76	124.86	20.31	840.56
Sh_LB	7,633	42.15	14.34	3.74	82.01
$BRANCHES$	7,633	5.746	1.447	1.545	10.268
HHI	7,633	1.095	0.459	0.356	6.359
		Firm–specific explanatory variables			
RDK	7,633	0.022	0.062	0	0.568
$INNOVATION$	7,393	9.001	20.646	0	100
ROI	7,633	11.199	7.452	-9.573	40.120
$DEBT$	7,633	5.870	1.116	2.083	11.788
ML	7,584	5.967	3.669	1	30
$EXPORT$	7,603	0.725	0.447	0	1
$WORKERS$	7,633	69.057	84.913	11	500

Notes: The pooled sample of 7,633 observations is made by 2,947 observation from the first wave, 2,231 from the second one and 2,455 from the last wave.

Table 2: Innovation and Rationing by firm size

	Number of employees					Total	Obs.
	11–20	21–50	51–100	101–250	251–500		
INN	45.75	56.74	66.86	71.43	77.67	58.74	7,205
$INN \mid RDK > 0$	72.18	77.96	83.11	85.01	87.22	80.68	2,000
$PRODUCT$	16.32	25.32	34.83	41.60	45.87	27.90	7,205
$PROCESS$	39.68	48.58	56.05	60.65	69.55	50.41	7,633
RDK	1.77	1.94	2.79	2.94	2.93	2.24	7,633
RAT	17.55	15.17	14.65	11.96	8.41	14.90	7,633
$RAT \mid INN = 1$	18.64	16.38	14.53	11.66	7.76	15.09	4,660

Notes: The pooled sample of 7,633 observations is made by 2,947 observation from the first wave, 2,231 from the second one and 2,455 from the last wave.

Table 3: Credit market and instrumental variables: Pairwise Correlations

	FD_KM	$BRANCHES$	HHI	Sh_LB	FD_KM71	$BRANCHES36$	Sh_LB36	$CCB36$	$SB36$
FD_KM	1								
$BRANCHES$	-0.7014*	1							
HHI	0.128	-0.159	1						
Sh_LB	0.4160*	-0.3384*	-0.1636	1					
FD_KM71	0.6874*	-0.5656*	0.3044*	0.3263*	1				
$BRANCHES36$	-0.4902*	0.6321*	-0.1841	-0.1031	-0.3463*	1			
Sh_LB36	0.3458*	-0.5258*	0.0911	0.3591*	0.4826*	-0.4194*	1		
$CCB36$	0.0558	-0.0133	-0.1388	0.0727	-0.0338	0.0249	-0.2577*	1	
$SB36$	-0.3776*	0.5196*	-0.0382	-0.1527	-0.3534*	0.2935*	-0.3240*	-0.1073	1

Table 4: Adoption of Innovation: First–stage OLS regressions and second–stage Probit for the *CLR* test

	OLS First–stage on Endogenous variable				Second–stage Probit
	FD_KM	Sh_LB	$BRANCHES$	HHI	INN
FD_KM71	0.373***	-0.266	-0.170***	0.037***	
	[0.012]	[0.180]	[0.011]	[0.006]	
Sh_LB36	0.235**	56.582***	-1.271***	0.133***	
	[0.093]	[1.426]	[0.089]	[0.047]	
$BRANCHES36$	-0.067***	-0.437**	0.274***	0.061***	
	[0.014]	[0.217]	[0.013]	[0.007]	
$CCB36$	0.866***	14.617***	-0.352***	0.751***	
	[0.074]	[1.145]	[0.071]	[0.038]	
$SB36$	2.637***	1.726	0.553***	0.870***	
	[0.110]	[1.693]	[0.105]	[0.055]	
RDK	-0.038	1.404	0.007	-0.127**	4.875***
	[0.127]	[1.955]	[0.122]	[0.064]	[0.362]
ROI	0.000	0.002	-0.001	0.000	0.008***
	[0.001]	[0.016]	[0.001]	[0.001]	[0.002]
$EXPORT$	0.008	-0.287	-0.028	0.003	0.218***
	[0.018]	[0.278]	[0.017]	[0.009]	[0.038]
$WORKERS_{21-50}$	0.030	0.258	0.013	0.024**	0.226***
	[0.019]	[0.295]	[0.018]	[0.010]	[0.040]
$WORKERS_{51-100}$	0.009	-0.281	0.014	0.022*	0.452***
	[0.023]	[0.358]	[0.022]	[0.012]	[0.049]
$WORKERS_{101-250}$	-0.020	-0.816**	0.035	0.023*	0.572***
	[0.027]	[0.412]	[0.026]	[0.013]	[0.058]
$WORKERS_{251-500}$	-0.011	-0.701	0.044	0.021	0.707***
	[0.035]	[0.541]	[0.034]	[0.018]	[0.079]
Residuals FD_KM					0.224**
					[0.102]
Residuals Sh_LB					0.003
					[0.006]
Residuals $BRANCHES$					0.149
					[0.143]
Residuals HHI					-0.519*
					[0.281]
Observations	7,175	7,175	7,175	7,175	7,175
R^2	0.631	0.554	0.832	0.535	
F–test on instruments	0.000	0.000	0.000	0.000	
χ^2 test on residuals					0.217

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Regressions were run by using the software package Stata 10 with IVPROBIT command. The table reports in the first four columns the OLS coefficients, and the associated standard errors in brackets, of the first–stage regressions associated with the IV Probit estimates reported in column (2) of Table 5. The last column reports the coefficients of the standard probit regression augmented with the residuals from the first–stage estimates. The variable $WORKERS$ is split into five categories, with the reference category being 11–20 employees. Each regression includes (3) wave, (21) industry and (18) regional dummies and a constant, not shown for reasons of space. The bottom lines report the p–values of the test for the joint significance of all instruments of the residuals (the *CLR* test reported in column 2 of Table 5).

Table 5: Adoption of Innovation

Dep. Var.: $Pr(INN)$	Probit (1)	IV Probit (2)	IV Probit (3)	IV Probit (4)
FD_KM	-0.038	-0.244**	-0.287***	-0.241**
	[0.024]	[0.100]	[0.103]	[0.099]
$FD\_KM \times RDK$			3.074***	
			[1.067]	
Sh_LB	0.000	-0.004	-0.004	-0.004
	[0.002]	[0.005]	[0.005]	[0.005]
$Sh\_LB \times RDK$				-0.004
				[0.044]
$BRANCHES$	0.030	-0.125	-0.140	-0.121
	[0.025]	[0.142]	[0.143]	[0.142]
HHI	0.104**	0.620**	0.595**	0.606**
	[0.047]	[0.282]	[0.283]	[0.280]
RDK	4.813***	4.875***	-5.269	5.149***
	[0.534]	[0.365]	[3.512]	[1.997]
ROI	0.008***	0.008***	0.007***	0.008***
	[0.002]	[0.002]	[0.002]	[0.002]
$EXPORT$	0.223***	0.218***	0.215***	0.218***
	[0.037]	[0.038]	[0.039]	[0.038]
$WORKERS_{21-50}$	0.229***	0.226***	0.222***	0.226***
	[0.040]	[0.041]	[0.041]	[0.041]
$WORKERS_{51-100}$	0.459***	0.452***	0.455***	0.455***
	[0.049]	[0.050]	[0.050]	[0.050]
$WORKERS_{101-250}$	0.584***	0.572***	0.573***	0.572***
	[0.057]	[0.059]	[0.059]	[0.059]
$WORKERS_{251-500}$	0.717***	0.707***	0.702***	0.704***
	[0.078]	[0.081]	[0.081]	[0.081]
Observations	7,175	7,175	7,175	7,175
Wald test		0.000	0.000	0.000
F–test on regional dummies	0.000	0.006	0.005	0.006
F–test on industry dummies	0.001	0.000	0.000	0.000
CLR test		0.217	0.036	0.214
Sargan test		0.182	0.286	0.193

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Regressions were run by using the software package Stata 10 with PROBIT and IVPROBIT commands. Robust standard errors in brackets. Additional instruments include $CCB36$, $SB36$, $OP36$, Sh_LB36 and FD_KM71. The variable $WORKERS$ is split into five categories, with the reference category being 11–20 employees. Each regression includes (3) wave, (21) industry and (18) regional dummies and a constant, not shown for reasons of space. The F–test is on the joint significance of regional and industry dummies (p–values reported). As diagnostic, the Table reports the Wald χ^2 statistic for the likelihood ratio test of the goodness of fit of the regression, the p–value of the conditional likelihood ratio (CLR) test of exogeneity of the endogenous regressors and the p–value of the Sargan test for over–identifying restrictions (the null is the validity of the instrument set).

Table 6: Adoption of Process and Product Innovation

Dep. Var.:	Pr(PROCESS)			Pr(PRODUCT)		
	IV Probit (1)	IV Probit (2)	IV Probit (3)	IV Probit (4)	IV Probit (5)	IV Probit (6)
FD_KM	-0.230**	-0.244**	-0.225**	-0.171	-0.210*	-0.167
	[0.096]	[0.098]	[0.096]	[0.106]	[0.110]	[0.106]
$FD\_KM \times RDK$		0.682			1.533**	
		[0.749]			[0.754]	
Sh_LB	0.001	0.001	0.002	-0.016***	-0.016***	-0.015**
	[0.005]	[0.005]	[0.005]	[0.006]	[0.006]	[0.006]
$Sh\_LB \times RDK$			-0.033			-0.025
			[0.033]			[0.035]
$BRANCHES$	0.064	0.061	0.071	-0.328**	-0.344**	-0.326**
	[0.135]	[0.135]	[0.134]	[0.154]	[0.155]	[0.154]
HHI	0.614**	0.616**	0.598**	0.361	0.373	0.350
	[0.259]	[0.260]	[0.258]	[0.298]	[0.299]	[0.298]
RDK	2.302***	0.064	3.808***	3.721***	-1.297	4.891***
	[0.269]	[2.469]	[1.466]	[0.288]	[2.503]	[1.564]
ROI	0.010***	0.010***	0.010***	0.002	0.002	0.002
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
$EXPORT$	0.134***	0.134***	0.135***	0.340***	0.339***	0.340***
	[0.038]	[0.038]	[0.038]	[0.044]	[0.044]	[0.044]
$WORKERS_{21-50}$	0.189***	0.188***	0.189***	0.282***	0.280***	0.283***
	[0.040]	[0.040]	[0.040]	[0.047]	[0.047]	[0.047]
$WORKERS_{51-100}$	0.399***	0.399***	0.399***	0.426***	0.426***	0.425***
	[0.048]	[0.048]	[0.048]	[0.054]	[0.054]	[0.054]
$WORKERS_{101-250}$	0.507***	0.507***	0.507***	0.594***	0.594***	0.595***
	[0.055]	[0.055]	[0.055]	[0.061]	[0.061]	[0.061]
$WORKERS_{251-500}$	0.679***	0.678***	0.681***	0.727***	0.725***	0.731***
	[0.074]	[0.074]	[0.074]	[0.078]	[0.078]	[0.078]
Observations	7,603	7,603	7,603	7,175	7,175	7,175
Wald test	0.000	0.000	0.000	0.000	0.000	0.000
F–test on regional dummies	0.000	0.000	0.000	0.062	0.072	0.061
F–test on industry dummies	0.000	0.000	0.000	0.000	0.000	0.000
CLR test	0.004	0.006	0.009	0.051	0.075	0.010
Sargan test	0.944	0.970	0.928	0.473	0.481	0.445

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Regressions were run by using the software package Stata 10 with IVPROBIT command. Robust standard errors in brackets. Additional instruments include $CCB36$, $SB36$, $OP36$, Sh_LB36 and FD_KM71. The variable $WORKERS$ is split into five categories, with the reference category being 11–20 employees. Each regression includes (3) wave, (21) industry and (18) regional dummies and a constant, not shown for reasons of space. The F–test is on the joint significance of regional and industry dummies (p–values reported). As diagnostic, the Table reports the Wald χ^2 statistic for the likelihood ratio test of the goodness of fit of the regression, the p–value of the conditional likelihood ratio (CLR) test of exogeneity of the endogenous regressors and the p–value of the Sargan test for over–identifying restrictions (the null is the validity of the instrument set).

Table 7: Adoption of Process and Product Innovation: Ordered Probit model

	$PROD\&PROC$	$PROD$ / $PROC$	$NOINN$
FD_KM	-0.012**	-0.007**	0.019**
	[0.005]	[0.003]	[0.008]
$FD\_KM \times RDK$	0.216***	0.125***	-0.341***
	[0.070]	[0.040]	[0.109]
Sh_LB	0.000	0.000	0.000
	[0.000]	[0.000]	[0.001]
$Sh\_LB \times RDK$	-0.005	-0.003	0.008
	[0.005]	[0.003]	[0.008]
$BRANCHES$	0.006	0.003	-0.009
	[0.006]	[0.003]	[0.009]
HHI	0.019**	0.011**	-0.031**
	[0.009]	[0.005]	[0.014]
RDK	0.360	0.209	-0.569
	[0.236]	[0.137]	[0.373]
ROI	0.002***	0.001***	-0.003***
	[0.000]	[0.000]	[0.001]
$EXPORT$	0.057***	0.039***	-0.096***
	[0.008]	[0.007]	[0.014]
$WORKERS_{21-50}$	0.062***	0.032***	-0.094***
	[0.009]	[0.004]	[0.012]
$WORKERS_{51-100}$	0.129***	0.041***	-0.169***
	[0.012]	[0.003]	[0.013]
$WORKERS_{101-250}$	0.186***	0.033***	-0.219***
	[0.016]	[0.004]	[0.014]
$WORKERS_{251-500}$	0.254***	0.006	-0.260***
	[0.027]	[0.010]	[0.018]
Observations		7,175	
R^2		0.068	
Log–Likelihood		-6,971	
χ^2		1,345	

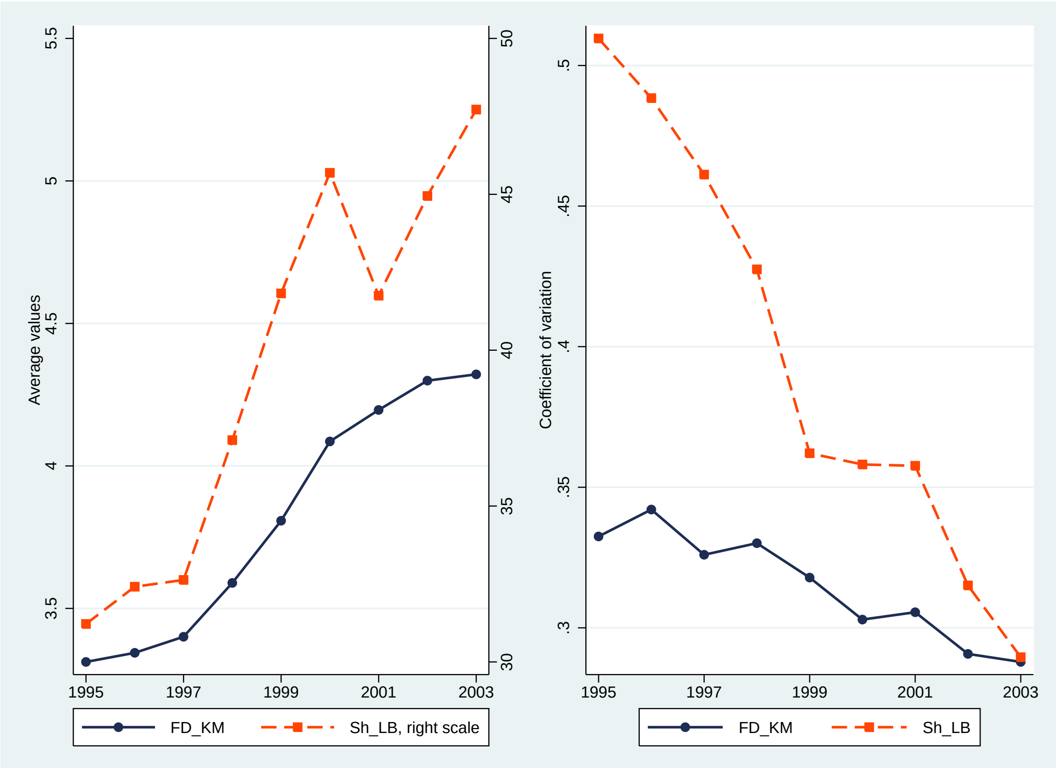
Notes: Marginal effects, calculated at sample means, are reported. * significant at 10%; ** significant at 5%; *** significant at 1%. Regressions were run by using the software package Stata 10 with OPROBIT command. Standard errors (in brackets) are corrected for intragroup ($province * wave$) correlation. The Table reports the marginal effects calculated at the averages (for dummy variables the coefficient is for discrete change from 0 to 1). The coefficients for (3) waves, (18) geographic and (21) industry dummies are not shown for reasons of space. All tests report p–values.

Table 8: Credit Rationing: Probit with Instrumental Variables

Dep.Var.: $Pr(RAT)$	Probit (1)	IV Probit (2)	IV Probit (3) $INN = 0$	IV Probit (4) $INN = 1$
FD_KM	0.005	0.677**	-0.107	0.520*
	[0.028]	[0.300]	[0.306]	[0.311]
Sh_LB	0.000	0.025*	-0.020	0.027
	[0.002]	[0.014]	[0.012]	[0.017]
$BRANCHES$	-0.080***	0.585	-0.371	0.498
	[0.030]	[0.363]	[0.306]	[0.432]
HHI	-0.028	-1.317**	0.147	-1.062*
	[0.045]	[0.536]	[0.562]	[0.547]
$INNOVATION$	0.003***	0.002**	0.002	0.002*
	[0.001]	[0.001]	[0.003]	[0.001]
ROI	-0.019***	-0.017***	-0.016***	-0.021***
	[0.003]	[0.003]	[0.005]	[0.004]
$DEBT$	0.254***	0.250***	0.272***	0.256***
	[0.018]	[0.021]	[0.029]	[0.029]
ML	0.015**	0.003	0.018*	0.001
	[0.006]	[0.009]	[0.011]	[0.012]
$WORKERS_{21-50}$	-0.093*	-0.108*	-0.114	-0.115
	[0.049]	[0.057]	[0.073]	[0.078]
$WORKERS_{51-100}$	-0.053	0.007	0.049	-0.013
	[0.061]	[0.075]	[0.105]	[0.111]
$WORKERS_{101-250}$	-0.206***	-0.097	-0.143	-0.155
	[0.074]	[0.097]	[0.134]	[0.123]
$WORKERS_{251-500}$	-0.405***	-0.250*	-0.395*	-0.278
	[0.110]	[0.140]	[0.214]	[0.180]
Observations	6,919	6,919	2,898	4,021
Wald test		0.000	0.000	0.000
F–test on geographic dummies	0.015	0.037	0.226	0.116
F–test on industry dummies	0.193	0.473	0.513	0.362
CLR test		0.006	0.304	0.046
Sargan test		0.101	0.003	0.398

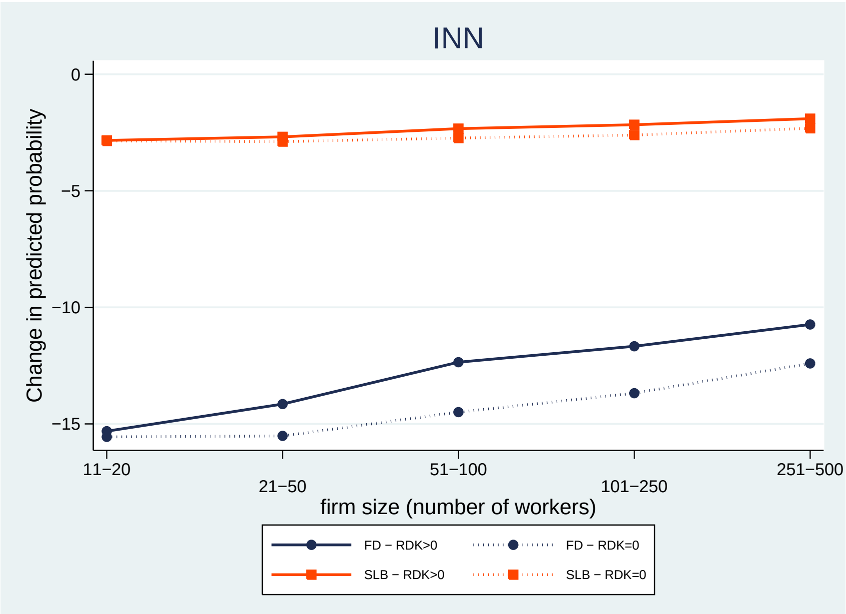
Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Regressions were run by using the software package Stata 10 with PROBIT and IVPROBIT commands. Robust standard errors in brackets. Additional instruments include CCB36, SB36, OP36, Sh_LB36 and FD_KM71. The variable $WORKERS$ is split into five categories, with the reference category being 11–20 employees. Each regression includes (3) wave, (13) sector and (5) geographic dummies and a constant, not shown for reasons of space. The F–test is on the joint significance of geographic dummies (p–values reported). As diagnostic, the Table reports the Wald χ^2 statistic for the likelihood ratio test of the goodness of fit of the regression, the p–value of the conditional likelihood ratio (CLR) test of exogeneity of the endogenous regressors and the p–value of the Sargan test for over–identifying restrictions (the null is the validity of the instrument set).

Figure 1: Evolution and variability of organizational structure indicators



Notes: The left–hand side diagram shows the average values of the 95 provinces of FD_KM (left scale) and Sh_LB (right scale). The right–hand side diagram plots the coefficient of variation for the 95 provinces, for each of the three indicators.

Figure 2: Changes in predicted probability due to variation in FD_KM and Sh_LB on innovation:



Notes: The diagram plots the effects of a variation from the first to the third quartile of FD_KM and Sh_LB on $Pr(INN)$, based on the estimates of columns 3 and 4 of Table 5, by firm size.

B List of variables

FD_KM, by province, is a measure of functional distance, computed as the ratio of branches weighted by the logarithm of 1 plus the kilometric distance between the province of the branch and that where the parent bank is headquartered, over total branches in province j (see Section 3 for details). Source: authors' calculations on Bank of Italy data.

Sh_LB, by province, is computed as the ratio of branches owned by large banks to the total number of branches operating in each province. Source: authors' calculations on Bank of Italy data.

$BRANCHES$, by province, is an indicator of operational proximity, computed as the number of bank branches in province j per 10,000 inhabitants (see Section 3 for details). Source: authors' calculations on Bank of Italy and ISTAT data.

HHI, by province, is the Herfindahl–Hirschman Index (ranging from zero to one) calculated on the number of branches in province j. Source: authors' calculation on Bank of Italy data.

INN, by firm, is a dichotomous variable which is equal to one if the firm introduced a product and/or a process innovation in the three–year period covered by each survey. Source: MCC Surveys.

$PRODUCT$, by firm, is a dichotomous variable which is equal to one if the firm introduced a product innovation in the three–year period covered by each survey. Source: MCC Surveys.

$PROCESS$, by firm, is a dichotomous variable which is equal to one if the firm introduced a process innovation in the three–year period covered by each survey. Source: MCC Surveys.

$INNOVATION$, by firm, is the percentage of sales coming from an innovative product. Source: MCC Surveys.

RDK, by firm, is the ratio between investments in R&D in year t and total capital stock at the end of year t–1. Source: Balance sheet data and MCC Surveys.

RAT, by firm, is a dichotomous variable which is equal to one if the firm states it is credit rationed and zero otherwise. Source: MCC Surveys.

ROI, by firm, is the Return on Investment, computed as gross operating earnings on invested capital. Source: Balance sheet data in MCC Surveys.

$DEBT$, by firm, is the measure of leverage, calculated as the logarithm of (1 + Debt–equity ratio). Source: Balance sheet data in MCC Surveys.

ML, by firm, is the number of banks with which the firm does business. Source: MCC Surveys.

$WORKERS$, by firm, is the number of workers. Source: MCC Surveys.