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Access to Capital Markets and the Geography of Productivity Leaders and Laggards

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Access to Capital Markets and the Geography of Productivity Leaders and Laggards

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Abstract

This paper examines whether access to the capital market of convertible and non-convertible bonds affects total factor productivity (TFP) for the population of Italian joint stock manufacturing companies, based in highly segmented local financial markets, between 2007 and 2017. The hypothesis, well grounded in the literature, is that long term capital favours investment in intangibles and other risky assets necessary for productivity growth. In order to identify this effect, we exploit the exogenous shock of the Italian banking deregulation of the mid-Nineties as an instrument for firm level access to capital, interacted with distance from logistic networks. These reforms changed the distribution of the type of branches at the local level, increasing the share of joint stock banks, which have high connections to international capital markets. This geographical reallocation of banking activities ultimately affected firms' financial structure, favouring their access to capital, even when based in peripheral financial areas. Firms which issued instruments of market debt achieved higher levels of productivity and a higher probability to reach top percentiles of productivity distribution.

JEL: R1, O4, G21

Keywords: productivity, bank deregulation, logistic networks dynamics

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1. Introduction

This paper examines how access to the capital markets of convertible and non-convertible bonds in highly segmented local financial markets affects total factor productivity (TFP) and the gap between leaders and laggard firms in productivity distributions in Italy. To overcome the endogenous firm-level decision to access capital markets, i.e. worst firms fail to recognize the importance of financial access for their performance, we exploit a banking sector reform of the nineties as an exogenous shock at the provincial level and its interaction with firm distance from a logistic network. The reform gradually changed the supply of different types of banks across Italian provinces, favouring the expansion of branches belonging to joint stock banks instead of mutual and state-owned ones. In segmented local financial markets, the presence of branches of credit institutions large enough to be connected to international capital markets can be very valuable: they support firms in having access to non-banking sources of finance even in more remote areas.

Our estimates show that firms with access to capital markets had higher productivity levels and a higher probability to move to higher percentiles of productivity distributions (to become leaders). The IV results show that a 10% increase in the value of bonds issued increases TFP by 2%, it increases the probability to move to the highest quintile of the productivity distribution by 1.5 percentage points (i.e. 25% of the probability to be in that quintile), increases the probability to be in the top decile of the distribution by 2.6 percentage points (26%) and the probability to be in the top ventile by 3.3 percentage points (16.5%). First stage results also show a robust positive link between financial development and access to capital markets and that such link gets looser as firms' distance from core travelling hubs increases. In other words, better financial market conditions improve firm performance if also coupled with access to core logistical nodes and other agglomerative factors. These findings are heterogeneous across firms and are likely to be driven by firms in the size band of 10 to 49 employees. For this latter group, a 10% increase in bonds increases TFP by 5%.

This contribution examines access to capital markets as one possible explanatory channel of the large and generally increasing gap between firms in the top percentiles of productivity distributions and other firms in lower deciles (Andrews et al., 2016). There is overwhelming evidence of a pattern of rising inequality in performance between the two groups, with laggards less and less able to converge to the top. We show that this pattern also clearly emerges for Italian firms.

According to Andrews et al. (2016) and Akcigit and Ates (2019) the lack of convergence between leader and laggard firms could partly be linked to slow patterns of technology diffusion and

insufficient investment generating intangible assets like R&D, brand recognition, presence in foreign markets.[4] These investments are very risky, involve large sunk costs and are hard to finance with bank loans, they require long-term capital, possibly equity or long-term market debt. Several studies have shown how financially constrained and highly leveraged firms are less likely to invest in intangibles (Demmou et al., 2019; Ahn et al., 2019; Nucci et al., 2005). Additionally, innovative activities are in general financed by equity and long-term debt (Carpenter and Petersen, 2002; Muller and Zimmerman, 2009; Brown et al., 2009; Eldridge et al., 2021), therefore access to non-bank long term financing can crucially affect firms' productivity. This latter point is precisely the link that we are exploring in this work.

There is an important geographical issue in firms' accessing corporate bonds' markets, especially for SMEs[5]. According to Barba Navaretti et al. (2019), the increasing global integration of financial markets and the prospect of the Capital Markets Union in the EU are likely to strengthen the concentration of financial activities in core areas and hence foster core-periphery patterns in finance, with firms in peripheral areas less likely to access capital markets. This is a well-known phenomenon even for access to banking. Several contributions show that firms in areas with higher agglomeration have better access to bank credit (Carmignani et al., 2019; Ganau, 2016; Lee and Brown, 2017; Mayer et al., 2021; Lee and Luca, 2019). Nonetheless, this geographical issue is certainly tighter for non-bank financing. Hence banks can play an important role in less connected areas. According to Barba Navaretti et al. (2019), in such areas, where the presence of branches of large, market driven and internationally connected banks is high, even though still far away from major financial markets, such branches may anyway help firms acceding alternative sources of financing.

The empirical analysis builds on a rich dataset for the universe of the Italian joint stock manufacturing companies between 2007 and 2017. For each firm the financial structure is observed and specifically its ability to raise funds from capital markets by issuing corporate bonds. Firm location is exploited to derive information on the characteristics of the banking market of the province and firm-level specific distance from a logistic network, as measured by distance from a local airport at the beginning of the period. Our sample of firm comprises over 328,207 firm-year observation, corresponding to 51,383 unique firms that we observe over the period of analysis.

[4] See also https://www.brookings.edu/blog/up-front/2022/01/20/gone-digital-technology-diffusion-in-the-digital-era/
[5] The existence of a geographical issue is also documented in a large body of evidence showing that financial markets tend to be highly segmented (Guiso et al., 2004 on Italy, Bircan and De Haas, 2020 on Russia, Cornaggia et al., 2015 on the US).

The identification strategy exploits the exogenous shock of the banking reforms of the early nineties in Italy on local banking markets in the provinces where firms are based. Public banks and many mutual banks were transformed into joint stock companies, subsequently privatised and then underwent a dramatic pattern of consolidation (see Appendix A for a thorough description of the institutional features of the banking reform). As large market-driven joint stock banks are connected to international capital markets, their local branches can favour firms' access to alternative sources of financing, by brokering soft information – resulting from long-term interactions with their clients – into hard one, to be conveyed to distant capital markets. In other words, such banks can effectively act as translators of soft into hard information.[6] The more joint stock banks at the local level, the higher we expect the access to capital markets for firms in the area. Moreover, the consolidation of the banking industry and the wider use of prudential requirements geared to the quality of credit, induced banks, especially large ones, to increasingly use standardized mechanisms of credit evaluation based on hard information along with relationship-based criteria and soft information. In essence, although excessive bank dependence might hamper firms' performance, banks themselves can support firms into diversifying their sources of funding.

Reforms of the banking system in local markets not only do they help broker soft into hard information but also shape firms' governance by improving reporting standards and making them more eligible for capital markets. This hypothesis is well supported by the literature. The availability of funds to firms varies with respect to the predominant type of banking organization (Rajan, 1992; Petersen and Rajan, 1994; Mayer et al., 2021). Close ties between lenders and borrowers in the relationship-based lending structure may facilitate more efficient communication and eliminate the information asymmetry that exists in the market. This is particularly important for small firms (Hombert and Matray, 2017). Relationship-based lending could however favour incumbents and prevent the entry of new firms (Rajan and Zingales, 2003). On the contrary, having larger competition among the lenders in arm's length type of lending improves firms' chances of securing loans as larger banking competition improves screening and monitoring procedures (Bai et al., 2018). Banking deregulation has an important role by changing the distribution of type of banking organization at the

[6] Petersen and Rajan (1994) show that soft information can improve the quality of screening in the bank decision to allocate capital. Yet physical proximity can also increase the market power of lending banks, as higher interests are charged because of information rents (Petersen and Rajan, 2002). A strongly related strand of literature has studied the comparative advantages of small and large banks in dealing with hard and soft information. The main prediction is that larger banks tend to have a comparative advantage in elaborating hard information, mainly because of the scale economies stemming from data collection and transmission and because of their more complicated managerial structure (Stein, 2002). Smaller banks, instead, with the leaner organization, are more capable of processing qualitative, and soft, information (Berger and Udell, 2002). Similar conclusions characterize the comparison of single vs. multimarket banks, and domestic vs. foreign banks. Single market banks tend to be concentrated in a limited area, and their knowledge of the local market allows them to have a comparative advantage in soft information (Degryse and Ongena, 2005; and DeYoung, Hunter and Udell, 2004). In a similar vein, foreign-owned banks are more skilled at dealing with hard information, and domestic banks tend to be more specialized in soft information lending (Detragiache et al., 2008).

local level. On the one hand, deregulation intensifies competition among banks, weakening established relationships and replacing the criteria for fund seekers from soft towards more hard information (Bai et al., 2018 and Hombert and Matray, 2017); on the other, it fosters entry of new firms (Black and Strahan, 2002, and Kerr and Nanda, 2009, for the US; Bertrand et al., 2007, for France) as it lowers entry barriers to access funds and eventually to the market. Alessandrini et al. (2009) for Italy and Zhao and Jones-Evans (2017) for the UK show that banking deregulation in conjunction with improvements in information and communication technologies softened the financing constraints for firms.[7]

The paper builds a time-varying measure of firm-level productivity and uses the outstanding value of convertible and non-convertible corporate bonds as an indicator of access to capital markets. In order to properly identify the effect of access on firm productivity it is necessary to isolate its impact from other factors. We have to deal with issues of reverse causality (*i.e.*, more efficient firms are more likely to have access to capital markets and to be less exposed to banks) and of firms' selection (*i.e.*, firms' entry decisions into a specific local market could be driven by the presence of adequate financial institutions). To address these concerns on identification, the following is carried out. First, any possible weakness in the identification of the effect is addressed by holding constant any other possible confounding factors. More specifically, results are robust to very stringent regression specifications where initial-firm-specific characteristics are held fixed over time, industry specific time trends (*i.e.* technological shocks), province fixed effects and regional time varying factors are controlled for. Second, the instrumental variable strategy is based on the exogenous variation induced on local markets by the reform. We obtain an exogenous time varying representation of the provincial banking markets by simulating the local growth of mutual and joint stock branches and allocating the 10 year-lagged nationwide yearly growth rates of branches using the initial exogenous shares of branches by province and type of bank in 1996-1998, in a very similar fashion to the Bartik methodology (see Goldsmith-Pinkham et al., 2020). Moreover, the simulated measure of policy reform is interacted with the firms' weighted distance of their location from airports to also examine the role of geographical proximity to logistical networks. This measure of firm-level distance from the networks can be considered exogenous to contemporaneous local productivity shocks as weights on the importance of the airport are measured at the beginning of our period of analysis, *conditional* on observable factors we control for. Therefore, results have a causal interpretation under the assumption that there are no relevant omitted variables that determine both the 10-year lagged

[7] Both Guiso et al. (2004) and Benfratello et al. (2008) use a reform of the local banking markets and specifically 1936 historical data as an instrument of local financial development. They find that branch density (number of branches per head) is positively related to innovation for a sample of Italian firms in the late nineties.

provincial bank distribution and the firm-level performance today. Furthermore, any possible threats to the exclusion restriction are taken careful care of, as the deregulation could have affected other factors (*i.e.* the supply of high school educated in the province, access to export networks or simply the financial culture)[8]. Results are robust to estimations based on balanced samples and to alternative definitions of firm performance and access to capital markets.

This paper contributes to the existing literature in several ways. First it specifically examines the role of finance in explaining productivity gaps between leaders and laggards (Andrews et al., 2016). Secondly, it focuses on the impact of access to capital markets on productivity, a different and not necessarily substitutable form of financing with respect to bank credit. Most of the literature has focussed on the role of bank credit for firm level performance (Aghion et al., 2010, Benfratello et al, 2008, Garcia-Macia, 2017; Caggese, 2016; Levine, 2005; Midrigan and Xu, 2014; Bircan and De Haas, 2020; Manaresi and Pierri, 2018; Moretti, 2014). Third, it looks at the joint role of local financial markets and distance from business networks for the access to capital markets. In this framework, local financial markets are especially important, given the high levels of geographic segmentation of these markets and the provincial concentration of high- performing firms. Although even this paper looks at the characteristics of the local banking sector, it examines how firm location is instrumental to the access of capital markets, while most contributions focus strictly on bank credit access (Moretti, 2014; Ganau, 2016; Carmignani et al., 2019). Distance is measured considering access to transportation networks, as recent literature has shown that it can have a direct effect on the quality of management (Baltrunaite and Karmaziene, 2021) where decisions to access capital markets are taken. Fourth, it uses firm-level balance sheet information (bonds) for the universe of Italian manufacturing companies and exploits a long time-series, contrary to other contributions, mostly focussed on access to banks based on firm level survey data, where firms were asked to self-report their level of financial constraints (Petersen and Rajan, 1994; Alessandrini et al., 2009; Lee and Luca, 2019). Finally, it uses a novel instrumental variable estimation that relies on the exogenous variation from the banking deregulation reform.

In what follows data and descriptive evidence of productivity patterns in the Italian territory and of firm average financial structures are provided. Then the empirical strategy and results are discussed.

[8] The local economic environment in which the firm develops is very important as it affects firms performance and behaviour (Glaeser et al., 1992; Ganau and Rodríguez-Pose, 2018; Cainelli, Ganau and Iacobucci, 2016) through several other channels than finance. Because of the controls introduced in the estimations, the effect of firms' distance from bank is expected to matter mainly for access to capital as firms exploit localization externalities by having more access to specialized suppliers (i.e. banks), while it does not have any direct effect on productivity, over and above that one observed through a better access to capital markets. Higher distance between lenders and borrowers decreases the lender's ability to collect soft information about borrowers, with negative effects on the probability to access credit, especially for SME (Bofondi and Gobbi, 2003; Agarwal and Hauswald, 2010; Guiso et al., 2004).

2. Data and descriptive statistics

Our analysis is based on the population of Italian manufacturing joint stock companies between 2007 and 2017 provided by Cerved from *Centrali dei Bilanci*. This includes an average of 29,837 observations per year varying between 26,892 in 2007 and 31,972 in 2017. The analysis is therefore done at the firm level. The unit of observations are headquarters, which is the one that matters for our analysis.[9] Following some sample restrictions related to the presence of detailed information on the firm location and on the financial variables (see Appendix B for information about sample construction), the final sample consists of 328,207 year-firm observations.[10]

We first compute labour productivity using the information on (real) value added from balance sheet data and the number of employees. Because the number of employees reported is missing for a large percentage of firms (57%) we use the same methodology as in Di Giacinto et al. (2014) and impute the firm specific number of employees deriving it from total labour costs. In particular, for all firms for which we have information on the number of employees, we computed the median of the distribution of average cost per employee within cells defined by sector (2 digit), region, local labour market (683), percentile of revenues and value added. We use this information to estimate the number of employees for the remaining firms by dividing their total cost of labour by the median average cost of the cell they belong to.

As for total factor productivity (TFP), we use a value-added based production function where inputs are measured as in De Loecker and Warzynski (2012): number of employees and (real) capital, measured by total fixed assets in book value.[11] We use the estimation methodology as suggested in Ackerberg et al. (2015) (ACF, hereafter).[12] We proxy material inputs with consumption and general expenses from balance sheet data and labour is one year lagged.[13] We run a total of 24 regressions,

[9] Corporate financing decisions are more likely to be made at the management and investor level (OECD, 2015, Didier et al, 2016). While this could create some sorting problems of firm decision to enter a local market, we deal with this issue in the next session when explaining the identification strategy. It should be however noticed that we do not have any information on firm affiliation with a business group.

[10] In Table B1, we report t-tests for differences in observable characteristics (regions and sectors) between our sample of analysis and the initial sample. Despite showing differences, these are observable characteristics we can control for.

[11] We have also used, as an alternative measure of labour input, labour costs. Estimation results are presented in Table C5 in Appendix C.

[12] See Appendix B for details

[13] Levinsohn and Petrin (2003) identify in the intermediate inputs a proxy for any unobserved productivity shock, shocks that could simultaneously affect input choices and firm performance. Wooldridge (2009) suggests that to solve any issues of simultaneity of firm's inputs decision the estimation should be implemented using GMM in a two-equation model. The equations are estimated simultaneously with same outcome and inputs but different instruments, allowing for the identification of coefficients on capital and labour in the first equation. The ACF is an additional advancement, proposing a methodology that uses a control function approach to control for unobserved productivity shocks. The latter can be expressed as a function of observables, using an inverted inputs demand

separately for each manufacturing 2-digit sector (SIC codes 10 to 33) and we control for year fixed effects. In this way, we have a TFP distribution for each sector with comparable TFP measures across years. Additionally, we derive TFP measures corrected by firm and time varying markups measured as in De Loecker and Warzynski (2012). Value-added, capital, material inputs and wage bills are deflated using industry-specific deflators. Figure 1 reports average productivity levels in logs between 2007 and 2017. We report three different measures of productivity: labour productivity defined as (real) value added over number of employees by firm, TFP and TFP net of mark ups, these latter using the ACF methodology. All measures follow similar trends, with deep dives in 2008, at the start of the financial crisis.

Figure 1. Average TFP, TFP net of markup and labour productivity

Source: Cerved data, years 2007-2017, TFP estimated using methodology by Ackerberg, Caves and Frazer (2015) and markups measured as De Loecker and Warzynski (2012). Labour productivity is measured as (real) value added from balance sheet data over the number of employees.

The Cerved data set provides all balance sheet information and several financial indicators. We can therefore observe firms' financial structure and their source of funding. In Table C1 of Appendix C we report all the descriptive statistics of the variables used in the analysis. For each firm we know the municipality where it is based and for the empirical analysis, we exploit the provincial clusters.[14] We use this geographical dimension because it allows us to combine the firm level information with

function (see Ganau and Rodríguez -Pose, 2018 for a detailed discussion). In our main results we use the ACF procedure, but we show that they hold even when using the Wooldridge (2009) methodology (Table C4).

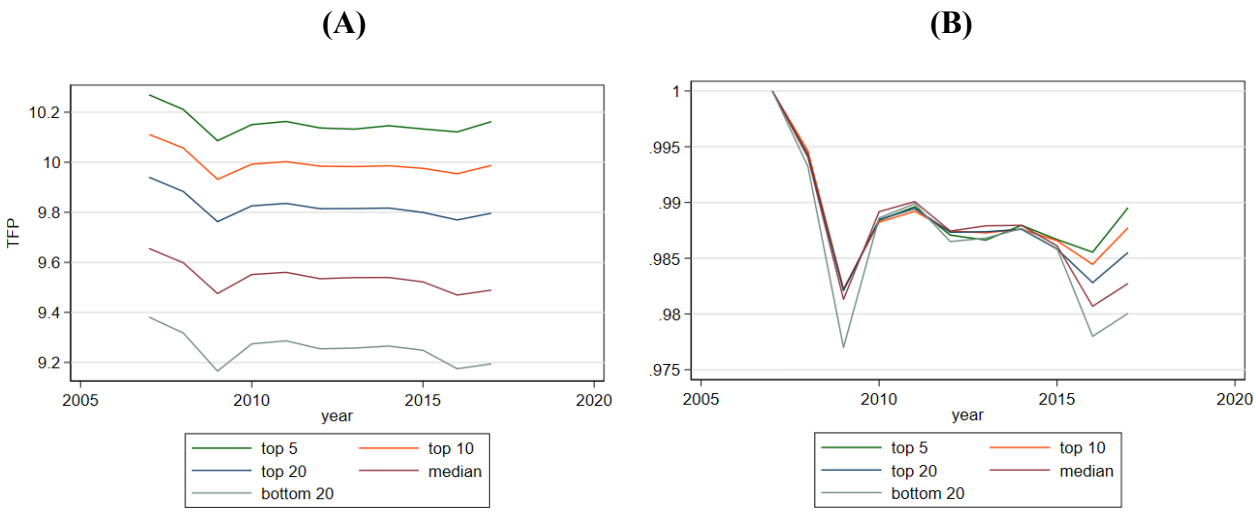
[14] Our final sample includes 92 provinces.

information on local banking activity, using data on the number and type of bank branches (joint stock or mutual bank) per province since 1996, from the statistical portal of the Bank of Italy.[15] [16]

2.1. Leaders and laggards

Leaders are defined as firms at or above the top 5th percentile of productivity distributions in each year and sector. Yet we also use other definitions of leaders, as those firms at the top 10th and top 20th percentile of the same distribution. To avoid selection problems due to sample size increasing over time, we keep the number of leaders at the top constant, despite its composition varies with time.[17] Laggards are all other firms below the top n^{th} percentile of leaders.

Figure 2. TFP levels (a) and time trends (b) for given percentiles of the TFP distribution (2007-2017)



Note: TFP measured using the ACF estimation procedure.

The leader-laggard patterns emerge clearly from Figure 2, which shows TFP levels across different percentiles between 2007 and 2017. There is a clear and persistent productivity gap between firms at the 95th percentile and the other firms. Hence leaders are considerably more productive than the rest of the group, including those performing relatively well (80th percentile). Also, starting from 2007, there is no evidence of productivity convergence. In line with what found by Andrews et al. (2016) for OECD countries, the gap increases between top performers and firms in other percentiles,

[15]Data can be found at: https://www.bancaditalia.it/statistiche/tematiche/moneta-intermediari-finanza/intermediari-finanziari/index.html?com.dotmarketing.htmlpage.language=1

[16] Provinces' administrative areas fully overlap with the Chamber of Commerce (CC) territorial competences. Each firm registers at the CC of reference if their registration address is within that province. The CC of reference provides to firms within their area of competence all types of services and supports, including and not limited to financial. Provinces therefore represent a relevant administrative unit of analysis for firms. Moreover, this choice is in line with Guiso et al. (2004) showing that banking regulation was based on politically driven provincial schemes.

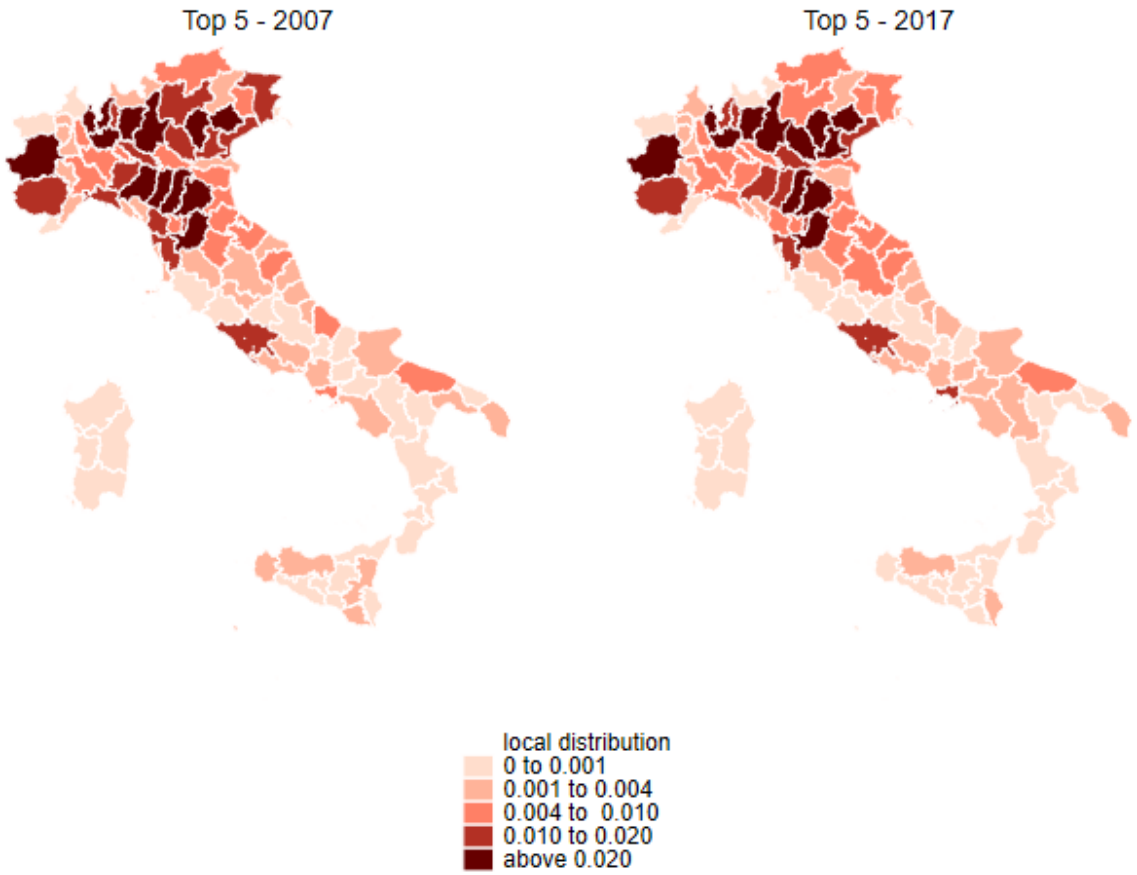
[17] Equal to the median of the distribution of the number of firms at the frontier in the whole period (Andrews et al., 2015).

especially those at or below the median, even though Italian leaders have not regained the pre-crises productivity level yet in 2017, as shown in Panel B of Figure 2.[18]

What is the geographical distribution of leaders and laggards? In Figure 3 we report the geographical distribution of firms in the top 5th percentile across Italian provinces. Leaders are highly concentrated in few provinces, mostly in the North and Centre of the country. This pattern is persistent, as we do not observe any major change between 2007 and 2017. In Appendix Figures C1 and C2, we also report the same maps for firms in the top 10 and in the top 20. We notice firstly that the distribution of firms in the top 5th percentile has become slightly more concentrated over time, while this is not the case when we look at the distribution of firms in the top 10th and top 20th percentile. Secondly, as easily detected by the colours, firms in the top 10th and 20th percentiles are geographically distributed in a similar way as firms in the top 5th.

[18] This is probably also due to selection patterns. If we use a balanced panel, the productivity of leaders rises above pre-crisis levels.

Figure 3. Distribution of leaders across provinces – Top 5



Note: Leaders' distribution across provinces. The unit of analysis is the province, and in each unit we report the share of leaders in that province over the total leaders in Italy, in 2007 and in 2017 separately. Leaders defined using the same methodology as Andrews et al (2016), where the number of firms is constant across years and defined as the median number of firms in the top 5th percentile. TFP defined using the ACF (2015) method.

2.2. Finance and Productivity

How far TFP levels and gaps between leaders and laggards are related to access and use of finance? According to Andrews et al (2016) and Akcigit and Ates (2019) the lack of convergence between frontier and laggard firms could partly be related to slow patterns of technology diffusion. More generally, productivity growth is frequently linked to investment generating intangible assets like R&D, brand recognition, presence in foreign markets.[19] These investments are very risky, involve large sunk costs and are hard to finance with bank loans. Highly leveraged firms with a high degree of bank dependence are less likely to have access to capital markets for equity finance or long-term corporate bonds. The financial structure of firms can be a sign of how much firms have been able to access diversified financial sources. At the same time, it indicates their viability for future access to finance.

[19] See also https://www.brookings.edu/blog/up-front/2022/01/20/gone-digital-technology-diffusion-in-the-digital-era/

In Table 1, we start by descriptively comparing the financial structure of leaders and laggards. The measures of financial structure we look at are the average bank debt, the average total bonds issued (convertible and non-convertible), a measure of access to capital markets (dummy variable taking value 1 if the firm issues corporate bonds, 0 otherwise), average total debts and the ratio between total bonds and total debts. We use the three definitions of leaders as previously discussed. As expected, laggards have higher values of bank debt and lower values of bonds (even as share of total debts) and the share of firms that have access to capital markets is always higher for top performing firms, which are in general also more leveraged.

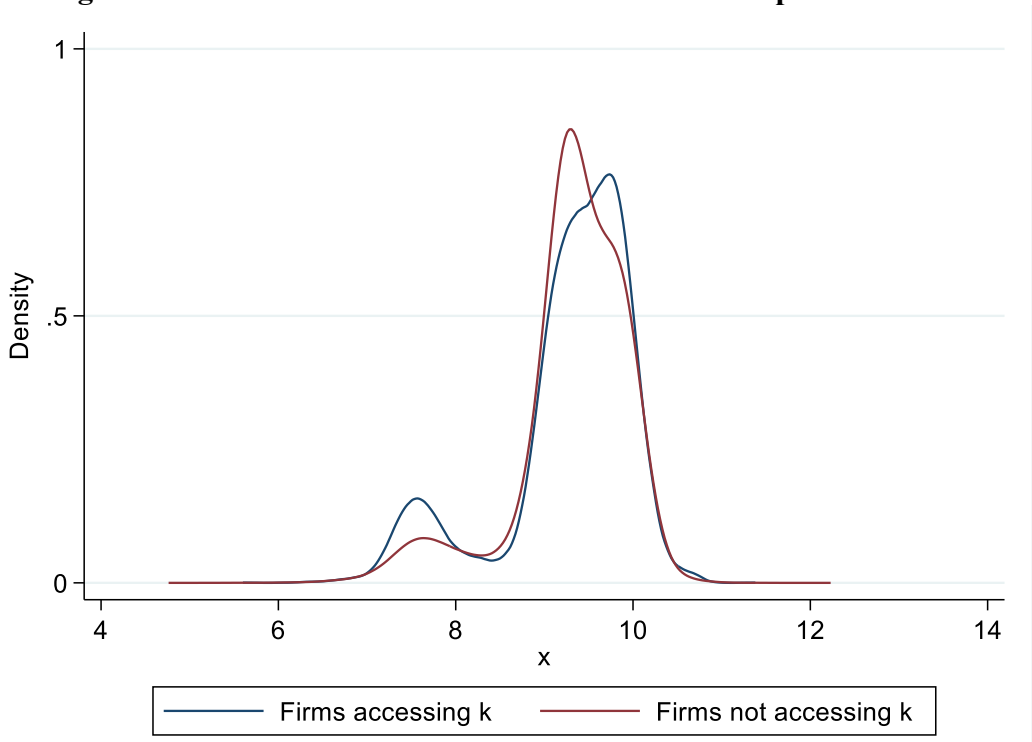
Table 1. Average financial structure along the TFP distribution

	Leaders	**Laggards**	**Difference (2) - (1)**
	(1)	(2)	(3)
	Panel A: Top 5		
Bank debt (€)	1,600,327	1,753,714	153,387***
Total bonds (€)	73,275	53,131	-20,144**
Access to capital markets (dummy)	0.025	0.024	-0.001
Average total debts (€)	6,643,256	4,857,445	-1,785,811***
Ratio of total bonds on average total debts	0.006	0.004	-0.002***
Observations	18,515	309,692	
	Panel B: Top 10		
Bank debt (€)	1,654,908	1,756,374	101,466***
Total bonds (€)	73,304	51,879	-21.425***
Access to capital markets (dummy)	0.027	0.024	-0.003***
Average total debts (€)	6,360,052	4,782,275	-1,577,777***
Ratio of total bonds on average total debts	0.006	0.004	-0.002***
Observations	36,593	291,614	
	Panel C: Top 20		
Bank debt (€)	1,786,849	1,733,289	-53,560*
Total bonds (€)	69,954	49,848	-20,106***
Access to capital markets (dummy)	0.027	0.023	-0.004***
Average total debts (€)	6,203,616	4,607,352	-1,596,263***
Ratio of total bonds on average total debts	0.005	0.004	-0.001***
Observations	72,135	256,072	

*Note: Cerved data, 2007-2017, Authors' calculations. Column (3) shows the difference between column (2) and (1) and if statistically significant: *** p<0.01, ** p<0.05, * p<0.1.*

Our main variable of interest with regards to the financial structure of firms is whether they access capital markets and specifically whether they issue corporate bonds. In our data set we have balance sheet information on the value of convertible and non-convertible bonds issued. In Figure 4 we graphically show the TFP distributional differences between firms that have accessed capital markets and firms that have never had this opportunity: the graph clearly hints to the fact that the TFP distribution of firms that do not have access (red line) is slightly shifted to the left. Moreover, the differences in the probability to be at the top 20th, 10th and 5th percentiles of the TFP distribution between firms with access to capital markets and firms without is positive and statistically significant: firms with access have a probability of 24% vs a probability of 21% for firms without access to be in the top 20th, 12% vs 11% to be in the top 10th and 5.8% vs 5.6% to be in the top 5th.

Figure 4. TFP for firms with and without access to capital markets



Source: Cerved data, years 2007-2017. TFP estimated using methodology by ACF (2015) and markups measured as in De Loecker and Warzynski (2012).

Table 2 reports some descriptive statistics for firms that have a positive value of bonds in their balance sheet and by size measured at the beginning of the period of the analysis. The share of firms that have access to capital markets is 3.1%, they have an average value of bonds of 2.2 million euros and a median value of 1 million, because of the long right tail of the bond distribution. When looking at access by firm size it emerges that the share of firms with access (column 1) increases with size, and it is higher in larger firms (more than 250 employees) where 14.7% of them have bonds in their balance sheet. In this latter group the average total bond value is much higher (14 million euros).

Table 2. Firms with access to capital market

	Access to capital markets (dummy)	Number of firms with access to capital markets	Mean value of total bonds (€)	Median value of total bonds (€)
	(1)	(2)	(3)	(4)
Whole sample	0.031	1,577	2,248,285	1,000,000
Less than 10 employees	0.006	130	726,456	248,930
Between 10 and 49 employees	0.030	709	1,233,208	780,000
Between 50 and 249 employees	0.131	675	2,538,813	1,300,000
250 or more employees	0.147	63	14,818,994	5,493,765

Note: Cerved data, 2007-2017, Authors' calculation. Size defined in the first period of observation in the dataset. We include firms that show a positive value of bonds at least once during the sample period.

3. Empirical Specification and Identification

The aim of this work is to estimate the link between changes in financial structure and firm level outcomes, productivity or the probability to be a in the 5th, 10th and 20th top percentile of the productivity distribution that we will refer to probability to be leaders, for simplicity.

We therefore estimate:

$$y_{ipkt} = \beta Access\_K_{ipkt} + \rho X_{ipkt} + \delta_p + \gamma_k \times \tau_t + \varepsilon_{ipkt} \quad (1)$$

The outcome variable y_{ipkt} is defined for each firm *i* at time *t* in industry *k* and based in province *p*. We use two outcome variables: TFP (net of markups) and the dummy variable indicating if the firm is a leader or not.[20] The variable of interest ($Access\_K_{ipkt}$) is a measure of access to capital markets,

[20] When the outcome variable is nonlinear (probability to be leaders) the model is estimated using a (IV) linear probability model.

defined either as the log of the value of outstanding bonds[21] (both convertible and non-convertible) at the firm level or as a dummy equal to 1 if the firm has a positive value of bonds in its balance sheet. Therefore, our coefficient of interest β measures the impact of firm level access to capital markets on the level of TFP or on the probability to be a leader. The vector X_{ipkt} includes age, firm controls measured in the first year of observation of the firm (revenue-growth in the first 3 years since birth, patent investment and size) along with a set of time-variant region level controls (value added per capita, share of individuals with tertiary education and employment rates). The firm level variables capture some initial measures of unobserved firm quality. It has been shown that sufficient revenue financing can be considered a good predictor of survival for newly founded firm but also of general firm performance as it is inversely linked to the probability of default in bank loans (Laitinen, 1992; Soto-Simeone et al., 2020; Cole and Sokolyk, 2018). Blundell et al. (1995) propose using firm-specific 'level effects' based on historic patenting activity, and we follow this alternative to capture firm-level heterogeneity, including firm-level experience, absorptive capacity and other unobservables. Given the strong link found in the literature between innovation and financing (Didier et al., 2021), historic patenting activity allows us to control for those unobserved factors that could drive both access to finance and firm performance. Finally, we control for firm size given the importance and debated role firm size has on performance and access to capital markets: recent literature has in fact shown that smaller firms' faster growth than larger ones depends on their access to capital markets (Didier et al., 2016). To avoid any endogeneity issues of these variables that simultaneously vary with our dependent variable we measure them at the beginning of the period. Finally, some of our results could simply reflect differences in firm age between firms that have access to capital markets and firms that do not, we therefore control for firm age in each specification.[22] We control for time-invariant province effects δ_p and industry-specific year effects $\gamma_k \times \tau_t$, to account for fixed differences across provinces (*i.e.* economic, institutional, cultural) and time shocks in the outcome variables at the industry level.[23] We run the above specification on the full sample of firms in the manufacturing sector in Italy and we cluster standard errors at the provincial level.[24]

[21] We use log(1+bonds). We provide alternative measures following Card et al. (2020) and Bahar and Rapoport (2018). We use the inverse hyperbolic sine (*asinh*) defined as $\log[bonds + \sqrt{bonds^2 + 1}]$. The *asinh* transformation is used with the same aim to accommodate for firms with zero bonds. In fact, the linear monotonic transformation behaves similarly to a log-transformation, but it is defined at zero and the interpretation of estimators of the regression is similar to the log-transformed outcomes (Bellemare and Wichman, 2020). Estimation results are available in Appendix Table C6.

[22] Didier et al (2016) show that among firms that access capital markets, young firms tend to expand faster than more mature ones.

[23] As noted by Rajan and Zingales (1998) there are systematic differences across sector in firm dependence from external sources of finance. Controlling for the interaction between industry and year dummies takes care of these differences.

[24] Despite the variable of interest ($Access\_K_{ipkt}$) varing at the firm level implying no need to cluster the errors as the treatment is assigned at the firm level, the decision to cluster standard errors at the provincial level is motivated by the fact that in the experimental design - as described in the following section - the assignment mechanism of the treatment is at that provincial level (Abadie et al., 2017).

Any time invariant province specific factor – including average industrial composition, average level of human capital or average level of local financial culture – affecting firm level of TFP or the probability to upgrade as leaders are controlled for by provincial fixed effect, δ_p . This is particular important in our specification as more developed provinces may attract better financial institutions, affecting firm access to capital markets. Similarly, an average better supply of human capital in the province can also affect firm TFP growth. Province fixed effects purge our results from any human capital and any other province-related time-invariant confounding factors. Additionally, a within province estimator also reduces some reverse causality concerns, as any of these latter arguments must be valid in deviations from the province specific average.

In our specification we also include (3-digit) sector-time dummies interacted with year dummies to control for any sector time specific factor affecting the performance of Italian firms. This set of dummies control for any time-varying technological shock to productivity that is common to all firms in that specific 3-digit sector. In fact, $\gamma_k \times \tau_t$ account for unobserved sector specific demand shocks that require some firm adjustments, eventually affecting firm-level productivity.

While the above discussed specification is already very restrictive, we also provide evidence on the role of access to capital on productivity by additionally saturating our specification with firm fixed effects. It should be noted that most of the overall variation (70%) observed in both independent variables (log bonds and dummy for access to capital) comes from the between-firm variation, making it very hard to identify any statistically significant effect: accessing capital markets is very likely to be an absorbing state and the actual value of bonds does not vary much within firms over time. Moreover, the use of firm fixed effects may not be appropriate in this context as having a high within-firm variation in the access to capital markets is associated with lower probability to be leaders. A simple correlation analysis shows a negative correlation between the probability to be in top 5th percentile of the distribution and the firm level variation in access to capital. We therefore identify the effect exploiting the between firm variation in access to capital and performance within the same province and industry*year fixed effects. We run two additional checks. We include samples of firms that are more stable over time (*i.e.*, firms observed for at least 3 consecutive years and, alternatively, firms that are observed throughout the period-11 years) and we also use as outcome variable the residuals from a regression of TFP/probability to be leaders on firm fixed effects, to net out any unobserved heterogeneity, at least from firm performance. In both cases, results are confirmed.

3.1. Identification: the IV strategy

Despite all the controls, we still have some concerns regarding our identification. First, we may encounter an issue of reverse causality: access to capital markets may result from higher firm performance. As discussed in the previous section, the rich set of fixed effects (δ_p and $\gamma_k \times \tau_t$) and of firm-level and regional-level controls (X_{ipkt}) included in equation (1) may reduce this concern, but we may still have the issue that firms whose productivity grows with respect to the time-invariant provincial average are more able to access better financial institutions. Efficient firms are more likely to have access to capital markets, being less leveraged and less exposed to banks.

A second concern is that firms may choose where to locate, therefore we may not be able to disentangle the effect that comes from an *exogenous* change in the access to capital markets from an *endogenous* firm's entry decision into a specific province following considerations regarding the quality of financial institutions. Following a positive productivity shock, firms may decide to relocate in areas where they could have better access to capital markets, therefore endogenously change our variable of interest. This could lead to the wrong conclusion that firms with better access to capital markets have better productivity.

As we only observe the most recent location of the firm, we impute it to all previous periods. By keeping firm location constant over time, we may partially solve the location self-selection problem, yet by using the most recent location of the firm we encounter the risk of overestimating the effect of access to capital markets on firm performance: firms could have already endogenously moved to their final location. In fact, time-varying province specific shocks could have endogenously induced firms to move to specific local markets that are also served by better financial institutions.

For these reasons, we use an instrumental variable strategy to estimate equation (1), with the aim to address the two previous concerns. This strategy relies on a policy reform: the deregulation of the banking system in Italy, which took place in the first half of the 90s.[25] The reform created some exogenous variation in the availability of funds for firms. As shown by Guiso et al. (2004), the local dimension of financial markets is highly relevant especially for SMEs. Hence, local conditions considerably affect firms' access to funding.[26]

[25] In Appendix A, we describe in details the institutional ingredients of the Italian banking reform.
[26] Other earlier studies on the impact of financial development on growth are King and Levine (1993), Jayaratne and Strahan (1996) and Rajan and Zingales (1998).

We will exploit this exogenous shock in the characteristics of local financial markets at the level of Italian provinces and the firm's distance from a main logistic area as an instrument for the change in firms' access to finance. The basic intuition of our instrument is that financial development at the provincial level that happened in the 90s changed the local distribution of different types of banks (Figure 5) by increasing the share of joint stock banks. These banks are more likely to be connected to international capital markets but also require more hard information to allocate capital (Mayer et al., 2021). Increasing their presence at the local level supports capital allocation to firms by brokering soft information into hard one and convey it to distant capital markets. Soft information is crucial as it improves the quality of bank screening in the decision to allocate capital (Petersen and Rajan, 1994). The ability to collect soft information is however reduced by the increasing distance between the firm and the bank (Bofondi and Gobbi, 2003; Agarwal and Hauswal, 2010). We argue, however, that it is not only the firm-level distance from a major location that matters but it is its distance from a well-connected major location that has important consequences on firms' decision to access capital markets, as better logistic connections can improve the quality of the supply of managers that are more likely to support these decisions (Baltrunaite and Karmaziene, 2021).[27] As discussed in their work, the duration and the quality of managers' journey are important criteria for the potential candidates' decision to accept a board appointment and also firms prefer in-person meetings. In Figure C3 in Appendix we show the existence of a negative relationship between distance and firm access to capital or log value of bonds.

The choice of the unit of analysis is consistent with Guiso et al. (2004) who suggest that banking regulation, restricting branch openings until 1990, was based on politically driven provincial schemes. In fact, the number of banks' branches per province before the reform was strictly regulated, and it was very difficult to open new branches. Before deregulation almost 80% of total branches belonged to public commercial or saving banks. With privatization most banks were transformed in joint stock companies, although a large number of locally rooted mutual banks persisted in time. Because actual location of types of banks may be correlated with unobservable characteristics related to economic and demographic conditions, we simulate the local growth of bank branches using the initial geographic distribution in the provincial exposure to different types of banks to distribute at the provincial level the national growth of mutual and joint stock banks 10 years before our period of analysis. The deregulation, which took place only gradually in the first half of the nineties, massively affected the banking system only starting from the second half of the nineties. In 2006, almost 80% of the branches belonged to private national or foreign commercial banks. Figure 5 shows the rapid expansion of joint stock branches in Italy between 1996 and 2007, compared to the stable number of

[27] Given two provinces with the same level of joint stock banks, the one that is closer to a logistic network is expected to have a higher access to capital markets, also thanks to the better quality of firm managers that are attracted to the area by better connections.

mutual banks. According to Saccomanni (2008), between 1997 and 2007, 300 mergers and acquisitions took place leading to an increased concentration of assets and more than 50% of total banking assets changed hands. Hence the contemporary post 1996-1998 geographical distribution of the type of branches may be endogenous to the distribution of firms eligible for capital.

We therefore exploit the initial provincial allocation of branches at the start of privatization, ten years prior to the start of our period of interest, under the assumption that this allocation is unrelated to local unobservable shocks affecting outcomes in our period of analysis. In Figure C4 in Appendix C we map the initial provincial distribution of both joint and mutual banks in the period 1996-1998: these graphs show that there is not any evident concentration of joint stock banks in any specific area of the territory, while mutual branches are more likely to be found in the North-East part of the country. The correlation coefficient between the share of joint stock and mutual branches at the provincial level is 0.64. Firms in provinces with a large initial share of joint stock banks and to which our instrument exogenously and predominantly allocates the subsequent national growth of joint stock companies are expected to benefit more from the banking reforms and being better able to strengthen their financial structure.

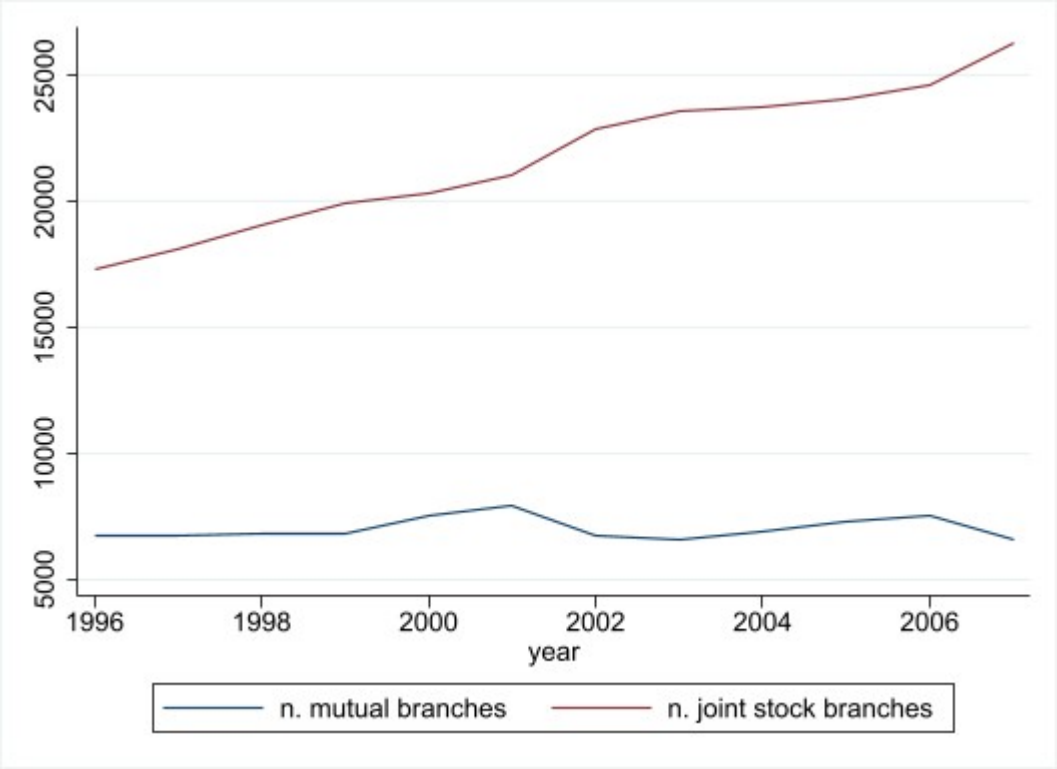
We build a measure of the provincial composition of the types of bank branches, joint stock or mutual banks, averaged between 1996 and 1998. Specifically, the local share we use in our measure is the average 1996-1998 share of each province *p* in the total number of branches of type *j* in Italy, where *j* refers to branches belonging to either joint stock or mutual banks.

Formally the local share of branches of each type is given by:

$$\overline{Share^{J}_{p,1996-1998}} = \frac{1}{3}\sum_{t=1996}^{1998} \frac{Branches^{J}_{p,t}}{Branches^{J}_{t}}. \quad (2)$$

To compute a time varying shifter, we use (2) to allocate to provinces the national growth of the two types of branches observed between 1997 and 2007, 10 years before our period of analysis. In other words, our shifter will contain lagged time changes at the national level yet allocated locally using the distribution of branches at the beginning of the privatization process. As it takes times for local financial market conditions to influence firm performance and especially the financial culture of firms, we exploit the time depth of our data on branches, and we compute their national growth with a 10-year lag with respect to productivity data.

Figure 5. Total number of banking branches by type - joint stock and mutual (1996-2007)



Source: Bank of Italy, number of branches by province between 1996 and 2007.

We therefore simulate the 10-year moving lagged distribution of the growth rate of branches by type and province as follows: [28]

$$\Delta SimulBranches_{pt-10} = \sum_J \overline{Share^J_{p,1996-1998}} \times \Delta Branches^J_{t-10} \quad (3)$$

$\Delta Branches^J_t$ is defined as $\frac{Branches^J_{p,t-10} - Branches^J_{p,t-9}}{Branches^J_{2007}}$.

The variable $\Delta SimulBranches_{pt-10}$ is the sum of mutual and joint stock national branch growth in year *t-10* allocated to province p following the share of branches at the period 1996-1998. As previously explained, we interact the simulated policy measure with firm distance from a logistic network. Specifically, we rely on the distance of the firm from the nearest airport, within a radius of 150 km. The distance is weighted by the inverse of the share of national passengers in 2007 (Percoco, 2010).

[28] For each year *t* in our sample, we look at the national growth rate by type of branches 10 years before.

We define d_i of firm *i* from the closest airport *a* (within 150km radius):

$$d_i = (1-k)\min\,(airport_a) \qquad (4)$$

where $k = \frac{passengers_a}{passengersITA(2007)}$.

Our measure of distance does not change over time, and it is the lower the closer the firm to the logistic network.[29] By keeping weights fixed over time, our definition of firm-level distance is exogenous to any provincial level shock that may affect both firms and airport relevance: airport development decisions can therefore be considered orthogonal to any economic unobservable shocks happening after 2007. We may still worry about whether the presence of the airport affected firms' operations (*i.e.,* improving transportation) or in general the local demand with a trickling-down effect to access to capital markets, causing a reverse causality problem. We tackle this issue by controlling local economic and institutional conditions (average local employment, value added and share of tertiary educated), as explained in equation (1).

The IV is:

$$Access\_K^{IV}_{ipkt} = \Delta SimulBranches_{pt-10} \times d_i$$

Our IV, therefore, varies at the firm and year level, like the endogenous explanatory variable, $Access\_K_{ipkt}$.

Our final aim is to identify the effect of changes in the firms' financial structure as a consequence of the reform on firm level measures of productivity growth. We estimate this using a 2SLS estimator. In the context of a 2SLS, it must be true that the reform, proxied by the simulated branches, impacted subsequent trends in firm performance only through its effects on the financial structure of the firm. Under this assumption, we are able to capture the *conditional* exogenous variation in access to capital markets induced by the reform and its interaction with firm distance from a logistically connected local market.

3.2. IV validity and diagnostics

The key identifying assumption is that the interaction between the pre-existing distribution of banks and the growth of joint stock vs mutual banks in the 10 years before our analysis and the firm-specific distance from a logistically connected area is uncorrelated with firm specific unobserved factors that

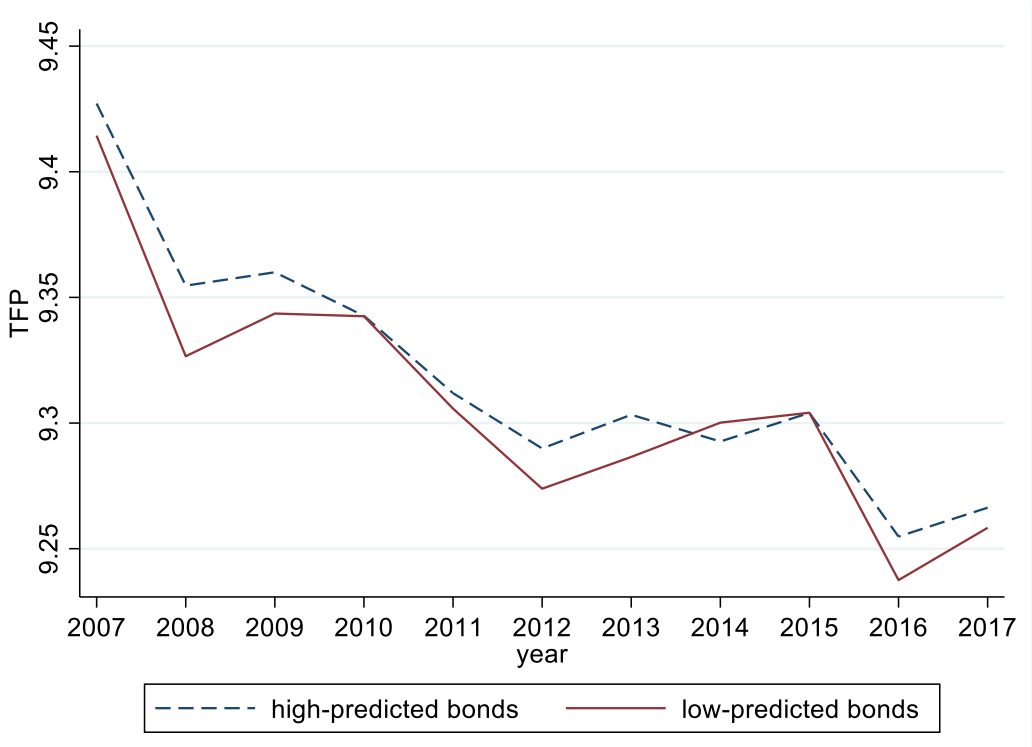
[29] We have a total of 30 airports in our sample. We report their location in a map in Figure C5.

could affect firm performance in 2007-2017. We could still have some threats to identification. The main issue is the persistence of local economic shocks overtime that could affect both firm performance and its access to capital markets. For this reason we provide some checks.

Firstly, by controlling for province fixed effects, our identifying variation is across firms that are geographically close to each other within similar local economic and institutional conditions but are different in their distance from the logistic network.[30]

Figure 6 shows some suggestive evidence of the evolution of the raw data on the TFP over time (one of the outcome variables). We have divided firms in two groups based on the average value of predicted bonds using the IV (Anelli et al., 2021).[31] We plot the average TFP value for firms with high-predicted value of bonds (dash line) and low-predicted value of bonds (solid line). We first notice that, on average, firms with higher predicted value of bonds are also more likely to have higher values of TFP. Secondly, the two groups have very similar trends.

Figure 6. TFP values by firms with low or high predicted bonds

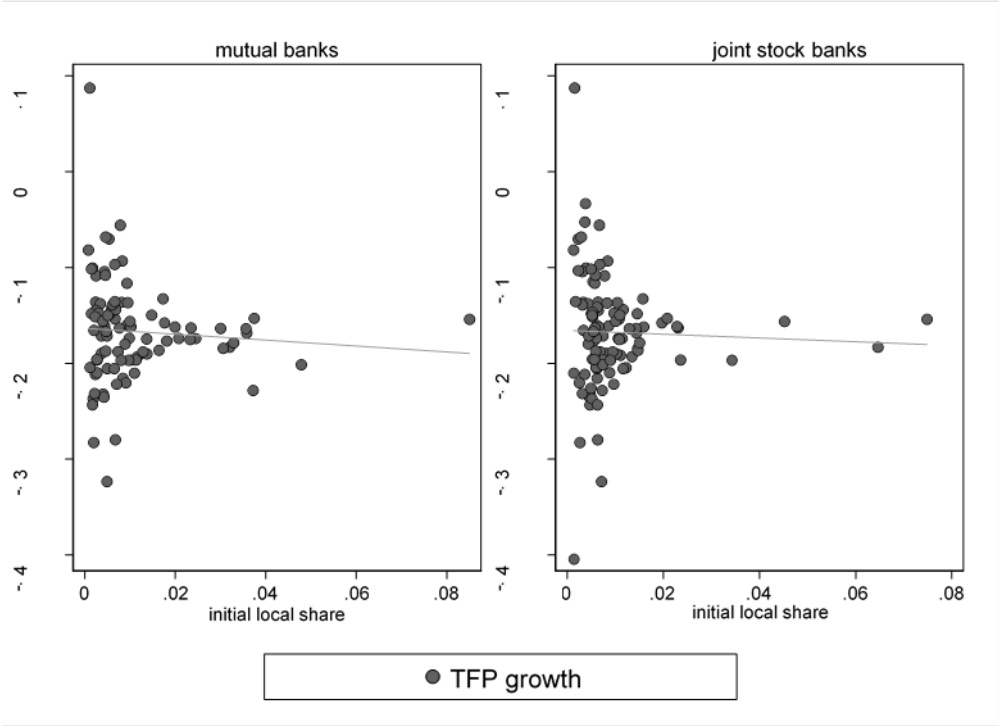


The IV is constructed like a Bartik instrument (Goldsmith-Pinkham et al., 2020). We in fact combine two sources of variation: the cross-sectional distribution of bank branches provincial shares by bank typology in a specific point in time (share component) and the national branch growth in period *t-10*

[30] We take for example the province of Milan (Lombardia). Within Milan, our measure of distance between firms and the closest airport varies between 0.72 km and 63km; in the province of Salerno (Campania) distance varies between 6km to 133km.
[31] We have averaged the predicted values by province, year and 3-digit sector.

(the shift component). The identifying assumption is that the composition of branches by province in 1996-1998 (share component), at the start of the reform process, was still exogenous to contemporaneous local economic conditions.[32] Figure 7 hints to this by showing that there is no cross-province correlation between TFP growth between 2007 and 2017 and the local share of banks of each type, averaged between 1996 and 1998.

Figure 7. Correlation between TFP growth (2007-2017) and local share of bank branches per type (mutual and joint stock – average 1996-1998) per province

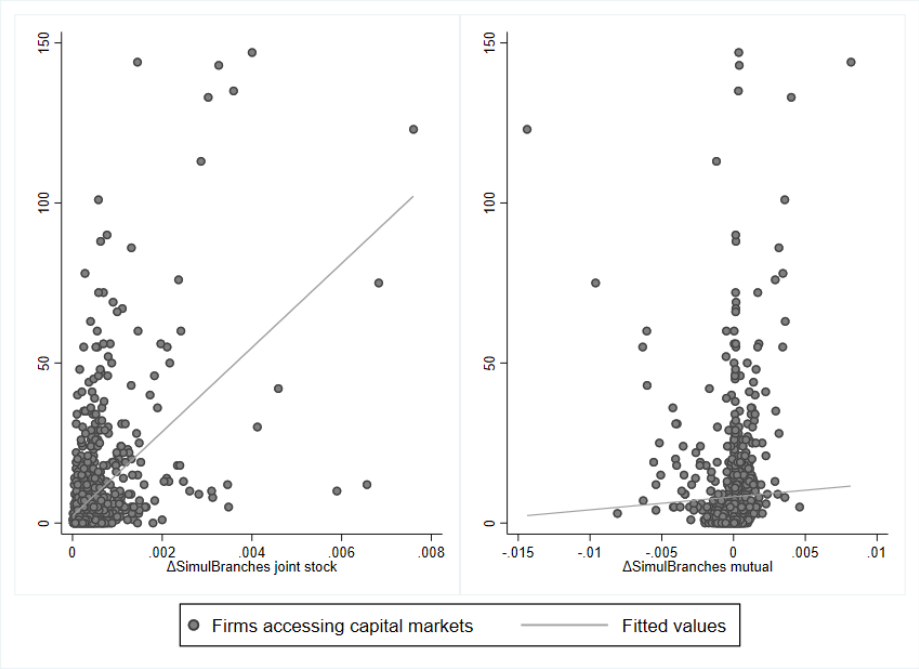


Source: Bank of Italy data on branches in 1996-1998 and Cerved data on TFP growth between 2007 and 2017. Left Panel reports the initial local share of mutual banks while the right panel the joint stock share by province.

In Figure 8 we report graphical evidence of the relation between the $\Delta SimulBranches_{pt-10}$ and access to capital, at the provincial and year level. Each dot on the y-axis represents the number of firms that accessed capital in a specific year *t* in province *p.* There is in fact a positive and statistically significant correlation between the increase in the simulated joint stock branches and the variable of interest (*correlation coefficient*= 0.14 *p-value*=0.000) while the correlation between access to capital markets and the simulated mutual branches is smaller and only marginally significant (correlation *coefficient*=0.05 and *p-value*=0.097).

[32] Goldsmith-Pinkham et al. (2020) show that a sufficient condition for identification when using the Bartik instrument is that the share component is uncorrelated with the error term. In their paper they provide additional diagnostics we do not show here.

Figure 8. Correlation between access to capital markets and simulated branches



Source: Bank of Italy and Cerved data. We report the total number of firms that accessed capital by province and year on the y-axis and the simulated branches in t-10 on the x-axis. The left panel shows the joint stock branches and the right panel the mutual banks.

The validity of the IV strategy relies on the untestable assumption of the exclusion restriction and that the variation induced by the instrument is therefore as good as random under these conditions. In order to provide some additional evidence on the robustness of our results, we propose some further checks. First, we estimate our model on a more stable sample of firms observed for at least three consecutive years: it will control for firm self-selection in and out of the markets. Second, as outcome variable we use the residuals from a regression of TFP/probability to be leaders on firm fixed effects: this exercise will net out firm-level heterogeneity from the dependent variable. Third, we investigate if the average effect is heterogeneously driven by a sub-group of firms that we define using the number of employees: the reform could have granted more capital market access to firms that were less likely to have it before the reform, by lowering entry barriers (*i.e.* SME as per Guiso et al., 2004). Finally, despite controlling for local economic and institutional time varying factors to account for any local demand shock, we take an additional step by reporting some evidence on the fact the deregulation mainly affected the channel studied in this paper and it did not directly affect other factors (supply of high educated individuals, R&D, etc…).

4. Main Results

4.1. Baseline results

We estimate equation (1) on all manufacturing companies in Italy between 2007 and 2017, using a sample of over 328,207 year-firm observations (51,383 unique firms). The main results using both OLS and 2SLS estimators are reported in Table 3. In Panel A we show results using the dependent variable log bonds while in Panel B we use the dummy access to capital markets, as previously defined. Within each panel, in each row, we use the four definitions of outcome variable (TFP -net of markups, probability to be in the top 5th percentile, probability to be in the top 10th percentile, and probability to be in the top 20th percentile). We show three different specifications: each odd column shows the OLS results while each even column the IV results of each specification. In each panel we report the KP Wald F-statistic for the IV robustness while first stage results for each endogenous variable are reported on Table C2 in the Appendix. In columns (1) and (2) we control for province (δ_p) and industry X year ($\gamma_k \times \tau_t$) fixed effects; in columns (3) and (4) we add firm level and local level controls (X_{ipkt}) and finally in columns (5) and (6) we drop province fixed effects and add firm fixed effects to account for firm unobserved heterogeneity.

First stage results (Table C2) show that the simulated measure of joint stock banks had a positive and higher effect than the measure of mutual banks on both log bonds and the dummy access to capital markets, while the effect of both their interactions with the variable distance are negative and significant: a standard deviation increase in the simulated branches of joint stocks increases the bonds by 2.26% (=100 x (exp(0.0013 x 51.128)-1)).[33] In support of our hypothesis on the role of distance, we find that the effect of financial market development declines with distance, as shown by the interacted term: the average effect of joint stock banks decreases by 0.3 percentage points each km away from the logistically connected area. Similarly, the probability to access capital markets increases almost 5 times more if there is an increase in the presence of joint stock banks with respect to mutual banks, showing that 1 standard deviation increase in the simulated joint stock branches increases the probability to access capital by 0.5 percentage points, a 25% increase with respect to the baseline probability (=0.02). Also in this case, the effect is decreased by distance from a logistic network by 0.077 percentage points each km away from the core area.

IV estimates show that access to capital markets positively affects firm performance. Solving the endogeneity issue flips the sign and increases the magnitude of the OLS estimates, hinting to the fact that the actual measure of access to capital markets as reported in the balance sheet may suffer from

[33] For descriptive statistics on the variables see Table C1.

Table 3. Access to capital markets and firm performance

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
			Panel A: log bonds			
Dependent: TFP (net markup)						
Log (total bonds)	-0.004***	0.094*	-0.004***	0.206*	-0.002***	0.040
	(0.000)	(0.055)	(0.000)	(0.107)	(0.000)	(0.032)
Dependent: Probability to be leaders (top 5)						
Log (total bonds)	-0.001	0.101***	-0.000	0.150***	-0.000	0.071
	(0.000)	(0.019)	(0.000)	(0.038)	(0.000)	(0.057)
Dependent: Probability to be leaders (top 10)						
Log (total bonds)	-0.000	0.184***	0.000	0.260***	-0.000	0.074
	(0.001)	(0.038)	(0.001)	(0.065)	(0.001)	(0.093)
Dependent: Probability to be leaders (top 20)						
Log (total bonds)	0.000	0.212***	0.000	0.332***	-0.001	0.129
	(0.001)	(0.055)	(0.001)	(0.103)	(0.001)	(0.155)
KP Wald F-statistic		6.496		7.636		2.083
			Panel B: Access to capital markets			
Dependent: TFP (net markup)						
Access to capital (dummy)	-0.054***	1.278	-0.053***	2.869*	-0.024***	0.462
	(0.006)	(0.789)	(0.006)	(1.531)	(0.005)	(0.470)
Dependent: Probability to be leaders (top 5)						
Access to capital (dummy)	-0.009	1.442***	-0.008	2.159***	-0.005	1.064
	(0.006)	(0.286)	(0.006)	(0.582)	(0.005)	(0.865)
Dependent: Probability to be leaders (top 10)						
Access to capital (dummy)	-0.005	2.621***	-0.003	3.738***	-0.004	1.184
	(0.009)	(0.564)	(0.010)	(0.987)	(0.007)	(1.429)
Dependent: Probability to be leaders (top 20)						
Access to capital (dummy)	-0.002	3.010***	0.001	4.747***	-0.011	1.903
	(0.011)	(0.803)	(0.011)	(1.556)	(0.009)	(2.304)
KP Wald F-statistic		5.612		6.029		1.788
Firm level controls	no	no	yes	yes	no	no
Regional level controls	no	no	yes	yes	yes	yes
Province fixed effects	yes	yes	yes	yes	no	no
Industry X year fixed effects	yes	yes	yes	yes	yes	yes
Firm fixed effects	no	no	no	no	yes	yes
Observations	328,207	328,207	316,284	316,284	321,892	321,892

*Note: Cerved data 2007-2017, Authors' calculations. Standard errors clustered at provincial level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Firm level controls: size at the beginning of the period, average sales growth rates in the first three years observed, age of a firm, and log of initial R&D expenditures. Regional level controls: value added per capita, share of people with tertiary education and employment rates.*

some measurement error we are correcting for with the instrument. IV results are however not significant when we include firm fixed effects. As previously discussed, the lack of significance is likely to be due to the low within firm variability of both log bonds and access to capital. In our preferred model (columns 3 and 4), the IV estimates show that a 10% increase in bonds increases TFP by 2%, increases the probability to upgrade among the top 5% of firms by 1.5 percentage points (30%), among the top 10% by 2.6 percentage points (26%) and among the top 20% by 3.3 percentage points (16.5%). Panel B also point to similar conclusions. Specifically, accessing capital markets, increases TFP by 2.8%.

In columns 5 and 6 of Table 3 we also report results controlling for firm fixed effects. As previously discussed, these results are imprecisely estimated even though they hint to a positive correlation between access to capital markets and firm performance. The reason of this imprecision is found in the fact that accessing capital markets is likely to be an absorbing state at firm level and the value of bonds does not vary much over time within firms. We discuss this issue in the following paragraph.[34]

4.2. Firm selection and heterogenous effects by size

As previously discussed, we test the validity of our approach by running the following checks. We firstly investigate whether firms that are more likely to entry and exit the market are the drivers of our results. We do this by focusing on the sample of firms that we observe for at least 3 consecutive years.[35] This check allows us to rule out the possibility that the variation we are observing in both access to capital and firm performance is not just driven by selection (*i.e.*, firms that experience a negative productivity shock are more likely to leave the market and mechanically less likely to access capital markets). Results on this sample are reported in Table 4 and the structure of table is the same as in Table 3. We are reassured by the fact that they survive also for this sample, results on the level of TFP are positive but imprecisely estimated. With the same purpose, we also report results where we firstly run regressions on the outcome variables on firm fixed effects and then use firm-level residuals from these regressions as outcome variables on our preferred specification. While this model is not perfect as we are only netting out firm unobserved heterogeneity from the outcome variables, it allows us to control for its effect on firm performance that may drive part of our results. These results are shown in Table 5 and they confirm the positive effect of access to capital markets on firm performance. The effect on TFP residuals is positive but not significant, while the effects on the

[34] As bank debt is an alternative measure of access to credit, we have also used the lagged measure of bank debt as a control in our regression. It should however be noted that we cannot use the same IV for both variables and also bank debt is likely to be endogenous to firm performance. We show these results in Table C7. Our main results, in particular those on the probability to be leaders are confirmed.

[35] We also look at a balanced panel of firms and results are confirmed (Table C8 in Appendix).

residual probability to be leaders are positive and statistically, with slightly smaller magnitudes if compared to the ones in Table 3.

Secondly, we investigate if the average effect is heterogeneously driven by sub-groups of the population. In Table 6 we report results for our preferred specification by size bands (0-10, 11-49, 50-250, above 250 employees) as defined in period t_0. The literature has in fact shown that financial market development could play a more significant role for certain type of firms defined by their size. There is in fact a consensus on the fact that financial market development can be beneficial especially for SMEs (Audretsch and Elston, 2002; Guiso et al., 2004; Fagiolo and Luzzi, 2006; Scellato, 2007; Beck et al., 2008; Didier et al., 2016). The effects are weaker for larger firms as they can more easily raise funds *outside* their local areas. For this reason, we believe that the effect that we observe as captured by compliers moved by the instrument is more likely to be found among smaller firms. Results are supportive of this fact. Moreover, the effect is significant for firms in the size group 10-49, in line with previous findings, and the effect is more robust for the probability to be leaders. The estimated effect of log bonds on the TFP level is positive but imprecisely estimated while estimates on the probability to be leaders are in all cases positive and significant and very similar in magnitude to the effects estimated in Table 3, suggesting that the average effect is driven by this group.

Table 4. Access to capital markets and firm performance- at least 3 consecutive years

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
			Panel A: log bonds			
Dependent: TFP (net markup)						
Log (total bonds)	-0.004***	0.110*	-0.004***	0.255	-0.002***	0.029
	(0.000)	(0.066)	(0.000)	(0.159)	(0.000)	(0.028)
Dependent: Probability to be leaders (top 5)						
Log (total bonds)	-0.001**	0.101***	-0.001	0.151***	-0.000	0.076
	(0.000)	(0.024)	(0.000)	(0.047)	(0.000)	(0.054)
Dependent: Probability to be leaders (top 10)						
Log (total bonds)	-0.001	0.184***	-0.000	0.266***	-0.000	0.086
	(0.001)	(0.047)	(0.001)	(0.078)	(0.001)	(0.090)
Dependent: Probability to be leaders (top 20)						
Log (total bonds)	-0.001	0.208***	-0.000	0.340***	-0.001	0.130
	(0.001)	(0.065)	(0.001)	(0.124)	(0.001)	(0.140)
KP Wald F-statistic		5.543		6.317		2.243
			Panel B: Access to capital markets			
Dependent: TFP (net markup)						
Access to capital (dummy)	-0.059***	1.518	-0.054***	3.603	-0.027***	0.382
	(0.006)	(0.934)	(0.006)	(2.319)	(0.005)	(0.420)
Dependent: Probability to be leaders (top 5)						
Access to capital (dummy)	-0.013**	1.444***	-0.011*	2.185***	-0.003	1.137
	(0.006)	(0.356)	(0.006)	(0.716)	(0.006)	(0.815)
Dependent: Probability to be leaders (top 10)						
Access to capital (dummy)	-0.011	2.639***	-0.007	3.856***	-0.004	1.299
	(0.010)	(0.687)	(0.010)	(1.208)	(0.007)	(1.372)
Dependent: Probability to be leaders (top 20)						
Access to capital (dummy)	-0.011	2.955***	-0.004	4.901**	-0.013	1.951
	(0.012)	(0.942)	(0.013)	(1.879)	(0.009)	(2.115)
KP Wald F-statistic		4.410		4.570		1.949
Firm level controls	no	no	yes	yes	no	no
Regional level controls	no	no	yes	yes	yes	yes
Province fixed effects	yes	yes	yes	yes	no	no
Industry X year fixed effects	yes	yes	yes	yes	yes	yes
Firm fixed effects	no	no	no	no	yes	yes
Observations	279,864	279,864	269,662	269,662	279,864	279,864

*Note: Cerved data 2007-2017, Authors' calculations. Standard errors clustered at provincial level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Firm level controls: size at the beginning of the period, average sales growth rates in the first three years , age of a firm, and log of initial R&D expenditures. Regional level controls: value added per capita, share of people with tertiary education and employment rates.*

Table 5. Access to capital markets and firm performance – TFP/probability residuals

	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
Panel A: log bonds				
Dependent: TFP (net markup)				
Log (total bonds)	-0.001***	-0.006	-0.000***	0.001
	(0.000)	(0.008)	(0.000)	(0.010)
Dependent: Probability to be leaders (top 5)				
Log (total bonds)	-0.000	0.011**	-0.000	0.018**
	(0.000)	(0.005)	(0.000)	(0.009)
Dependent: Probability to be leaders (top 10)				
Log (total bonds)	-0.000	0.021**	-0.000	0.027*
	(0.000)	(0.008)	(0.000)	(0.015)
Dependent: Probability to be leaders (top 20)				
Log (total bonds)	-0.000	0.018	-0.000	0.032
	(0.000)	(0.011)	(0.000)	(0.021)
KP Wald F-statistic		6.662		7.862
Panel B: Access to capital markets				
Dependent: TFP (net markup)				
Access to capital (dummy)	-0.007***	-0.090	-0.006***	0.003
	(0.001)	(0.121)	(0.001)	(0.141)
Dependent: Probability to be leaders (top 5)				
Access to capital (dummy)	-0.001	0.159**	-0.001	0.259**
	(0.001)	(0.077)	(0.002)	(0.129)
Dependent: Probability to be leaders (top 10)				
Access to capital (dummy)	-0.001	0.297**	-0.000	0.393*
	(0.002)	(0.122)	(0.002)	(0.214)
Dependent: Probability to be leaders (top 20)				
Access to capital (dummy)	-0.003	0.257	-0.002	0.448
	(0.002)	(0.157)	(0.003)	(0.303)
KP Wald F-statistic		5.754		6.238
Firm level controls	no	no	yes	yes
Regional level controls	no	no	yes	yes
Province fixed effects	yes	yes	yes	yes
Industry X year fixed effects	yes	yes	yes	yes
Firm fixed effects	no	no	no	no
Observations	321,894	321,894	310,251	310,251

*Note: Cerved data 2007-2017, Authors' calculations. Standard errors clustered at provincial level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Firm level controls: size at the beginning of the period, average sales growth rates in the first three years observed, age of a firm, and log of initial R&D expenditures. Regional level controls: value added per capita, share of people with tertiary education and employment rates.*

Table 6. Access to capital (bonds) and firm size

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	less than 10 empl		10 to 49 empl		50 to 249 empl		250 or more empl	
	Panel A: log bonds							
Dependent: TFP (net markup)								
Log (total bonds)	-0.004**	3.043	-0.004***	0.263	-0.002***	-0.171	-0.001	-0.053
	(0.002)	(3.689)	(0.001)	(0.171)	(0.001)	(0.202)	(0.002)	(0.052)
Dependent: Probability to be leaders (top 5)								
Log (total bonds)	0.007*	-0.151	0.001	0.127***	-0.001***	0.017	-0.001	0.067
	(0.004)	(0.361)	(0.001)	(0.038)	(0.000)	(0.035)	(0.001)	(0.065)
Dependent: Probability to be leaders (top 10)								
Log (total bonds)	0.011***	-0.180	0.003***	0.206***	-0.002*	-0.040	-0.003**	0.027
	(0.004)	(0.466)	(0.001)	(0.062)	(0.001)	(0.082)	(0.001)	(0.046)
Dependent: Probability to be leaders (top 20)								
Log (total bonds)	0.017***	0.242	0.003***	0.267**	-0.001	-0.049	-0.004**	-0.060
	(0.004)	(0.678)	(0.001)	(0.106)	(0.001)	(0.129)	(0.002)	(0.100)
KP Wald F-statistic		2.154		6.589		1.006		1.080
	Panel B: Access to capital markets							
Dependent: TFP (net markup)								
Access to capital (dummy)	-0.046*	41.325	-0.055***	3.397	-0.033***	-2.365	-0.019	-0.749
	(0.025)	(50.822)	(0.008)	(2.273)	(0.013)	(2.636)	(0.027)	(0.698)
Dependent: Probability to be leaders (top 5)								
Access to capital (dummy)	0.075*	-1.166	0.010	1.750***	-0.020***	0.133	-0.023	0.964
	(0.044)	(4.627)	(0.008)	(0.564)	(0.006)	(0.466)	(0.015)	(0.946)
Dependent: Probability to be leaders (top 10)								
Access to capital (dummy)	0.110***	-0.983	0.032***	2.847***	-0.024**	-0.876	-0.048**	0.450
	(0.038)	(6.743)	(0.012)	(0.933)	(0.012)	(1.278)	(0.020)	(0.678)
Dependent: Probability to be leaders (top 20)								
Access to capital (dummy)	0.189***	4.864	0.040***	3.659**	-0.016	-0.838	-0.066**	-0.900
	(0.044)	(10.667)	(0.014)	(1.546)	(0.017)	(1.821)	(0.029)	(1.402)
KP Wald F-statistic		1.388		5.152		0.904		1.199
Firm level controls	yes	yes	yes	yes	yes	yes	yes	yes
Regional level controls	yes	yes	yes	yes	yes	yes	yes	yes
Province fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Industry X year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Firm fixed effects	no	no	no	no	no	no	no	no
Observations	104,757	104,757	165,592	165,592	43,017	43,017	2,704	2,704

*Note: Cerved data 2007-2017, Authors' calculations. Standard errors clustered at provincial level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Firm level controls: size at the beginning of the period, average sales growth rates in the first three years observed, age of a firm, and log of initial R&D expenditures. Regional level controls: value added per capita, share of people with tertiary education and employment rates.*

4.3. Alternative channels

Our specification controls for local economic and institutional time varying factors to account for any local demand shock, we nevertheless further investigate the effect of the deregulation on other alternative channels (supply of high educated individuals, R&D, etc…). If any, they could represent a threat to the validity of the exclusion restriction, as the deregulation, despite being national, could have affected local markets differently. While we are aware that this is an untestable assumption, we can check if the change in the distribution of the bank branches had a direct impact on some economically relevant variables. We run the first stage regression of our main specification with different dependent variables. The policy change could have impacted on the supply of educated workers, as better financial institutions may attract better human capital; the access to export networks, as firms could benefit from more international credibility and networks; local innovation as provinces being less financially constrained could decide to invest more resources in R&D; and finally also on the household financial cultures, by improving access to credit also for families, eventually affecting consumption and demand. We therefore run a battery of regressions where we have the above variables, on the left-hand-side. Results are reported in Table 7. It reports the effect of the simulated branches on the provincial value of exports for years 2007 to 2017 (column 1) and regional value of R&D for years 2012 to 2017 (column 2). There are no significant effects of joint stock banks and mutual banks on the value of exports, nor on R&D. In columns 3 to 5, we report data from the Bank of Italy Survey on Household Income and Wealth for years 2008, 2010, 2012, 2014 and 2016 on the share of tertiary educated in the region and two plausible proxies of financial culture: the use of credit cards and the pro-capita amount of expenses paid with cash both averaged by year and region. Also in this case, there are no significant effects of joint stock banks on the share of tertiary educated, nor on any measure of financial culture.

Table 7. Bank reform impact on export, R&D, education and financial culture

	Export	R&D	Share of workers with tertiary education	Share of households having at least one credit card	Amount of monthly expenses paid in cash
	(1)	(2)	(3)	(4)	(5)
ΔSimulBranches mutual	-16.516	-110.831	-0.001	-2.800	-1,880
	(116.847)	(95.171)	(1.541)	(5.543)	(7,751)
ΔSimulBranches joint stock	-99.964	-62.638	-4.337	-26.554	-30,202
	(343.662)	(235.462)	(4.622)	(16.625)	(23,245)
Observations	966	109	97	97	97
R-squared	0.717	0.965	0.813	0.855	0.786

Note: Column (1): ISTAT data 2007-2017 for export at provincial level (92). The panel is unbalanced with an average of 88 provinces per year varying between 86 in 2007 and 85 in 2017. The outcome variable is normalised by provincial value added, and the regression includes province and year FE. Column (2): ISTAT data 2012-2017 for R&D at regional level (19). R&D is normalised by regional value added. Columns (3) – (5): Bank of Italy Survey on Household Income and Wealth data for 2008, 2010, 2012, 2014, 2016. Data are provided on regional level (20). The regional panel is unbalanced with some years missing for Valle d'Aosta, R&D data is missing for 5 years across different regions. In all regional regressions, columns (2)-(5), we control for region and year FE.

5. Conclusions

We find robust evidence of a positive relation between productivity and financial structure at the firm level. We study this using detailed information from Italian firms in the manufacturing sector for years 2007-2017. We start the analysis from the hypothesis that large private national and foreign joint stock banks, even though connected to local economies, do allocate credit according to standard procedures and hence help firms access capital markets. This long term process force firms to increase the transparency of their financial statements, strengthen their governance, enhance their financial structure and improve their creditworthiness in a way consistent with the requirements of international financial markets. Moreover, firms are also better advised and supported by internationally branched banks in entering such markets and issuing corporate bonds.

We identify the relationship between the exogenous variation in firms' access to capital markets and firm level productivity and the probability to be at the top of the TFP distribution using an instrumental variable strategy based on the exogenous variation induced on local markets by the reform that happened in the banking system in the Nineties in Italy. We also examine how far the location of firms, and specifically their distance from logistic networks and the characteristics of the banking market of the province where they are based, impact on such relationship between finance and productivity, hence strengthening core-periphery dynamics.

We find that firms with better access to capital markets, following an increase in branches of large joint stock banks in the provinces where they are headquartered, show faster productivity growth and a higher probability to be leaders. This pattern is consistent with the view that firms in less-connected areas are less likely to have access to high quality inputs and especially finance. We find that in general laggards make less use of capital markets and are more bank exposed than leaders. Access to capital markets can be considered a possible explanatory channel of the increasing gap between firms in the top percentiles of productivity distributions and other firms in lower deciles. Access to non-bank long term financing becomes important for firms' performance, by supporting firms in riskier yet more profitable investments (*i.e.*, R&D, new technologies). Local financial markets are especially important, given the strong concentration in few provinces of firms in the highest percentiles of productivity distributions. Public policies can play an important role on this trend by removing barriers and addressing financial constraints: policy makers should be aware of the importance of location even for accessing capital markets.

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Appendix A. The institutional setting of the Italian banking system 1996-2006

In the first half of the Nineties the Italian banking system undergoes a very deep process of restructuring, induced by the major exogenous policy shock of the privatization of the system of public banks. Moreover, between 1990 (Law 218/90, l. Amato) and 1993 (D. lgs. 385/93, Testo Unico Bancario) new banking regulations are issued, allowing banks to become universal, in the sense that they can exert directly or indirectly any banking activity, whereas previously they could only operate as highly specialized entities (e.g. Short term vs medium term lending)

Moreover, according to Carletti et al. (2005), since 1973, banks had been subject to a "portfolio requirement" and a credit ceiling for loans to the private sector. Banks had to hold a minimum amount of medium-and long-term government or government guaranteed bonds, and also there was an explicit quantitative ceiling on the amount of loans to the private sector. Until the 1990s, the main objective of the Italian banking regulation was to foster local development and to ensure financial stability.

According to the following table from Fiorentino et al. (2009), in 1990 57.2% and 18.5% of total assets and 48.5% and 28.6% of total branches were managed by public commercial and saving banks or by cooperative and mutual banks respectively. Just 20.5% of total assets and 22.4% of branches were run by private commercial banks, generally fairly small ones. In 2004, the process of privatization accomplished, 79.3% of total assets and 76% of total branches were managed by private commercial banks and another 5.8% of total assets by private foreign banks. The reminder of banking activities was still in the hands of cooperative and mutual banks in 2004.

Table 9: Structure of the Italian Banking System in 1990 and 2004

	1990					2004			
	No. of Banks	No. of Branches	Assets, million EUR [1]	Assets, share in %		No. of Banks	No. of Branches	Assets, million EUR [1]	Assets, share in %
Public-Sector Banks	6	2,449	134,664	20.1					
Banks of National Interest	3	1,459	86,466	12.9					
Savings Banks	84	4,695	162,427	24.2	Commercial Banks	243	24,045	1,879,945	79.3
Private Commercial Banks	106	3,981	137,362	20.5					
Cooperative Banks	108	3,290	95,004	14.2		36	3,745	228,532	9.6
Mutual Banks	715	1,792	29,096	4.3	Mutual Banks [2]	439	3,603	126,369	5.3
Group central institutions	5	5	15,875	2.4		—	—		
Branches of Foreign Banks	37	50	10.475	1.6		66	108	137,063	5.8
Total	1,064	17,721	671,409	100		784	31,501	2,371,909	100

Source: Banca d'Italia
2. "banche di credito cooperativo"
Public-sector banks ("Istituti di diritto pubblico"), Banks of national interest ("Banche di interesse nazionale"), Savings banks ("Casse di risparmio" and "Monti di credito"), Private commercial banks ("Banche di credito ordinario"), Cooperative banks ("Banche popolari"), Mutual banks ("Casse rurali e artigiane"), Group central institutions ("Istituti centrali di categoria").

Source: Fiorentino et al. 2009

In the pre-privatization phase the banking system had limited exposure to competition, as banks were not contestable (besides from other banks within the same institutional category), and credit allocation was highly likely to be captured by local or national political interests. With the start of the process of privatization and the introduction of the new banking law, public banks were gradually transformed into joint stock entities owned by banking foundations and subsequently part of their shares were floated on the market.

The process of privatization was fairly slow and actually implemented between 1993 and 1999. At the same time there followed a major process of concentration of banking assets. According to Saccomanni (2008), between 1997 and 2007, 300 mergers and acquisitions leading to an increased concentration of assets took place and more than 50% of market share in total assets changed hands. The number of banks declined from 935 to 806 and of banking group from 87 to 82. In 2007 the two largest banking groups (Intesa San Paolo and Unicredit) accounted for 35.4% of total banking assets and three other medium-large groups accounted for another 35.4%.

This pattern, to a large extent driven by an exogenous policy shocks, triggered major changes in the banking market: i) an opening up to market forces of a previously highly protected banking system; ii) an increase in banking productivity, especially following subsequent mergers and consolidation (Fiorentino et al., 2009); iii) a pattern of credit allocation less likely to be captured by local and national political interests; iv) the possibility for banks to offer their clients a fairly rich basket of financial products, including access to non-banking markets.

This double pattern of privatization plus consolidation also triggered a very rapid expansion of the banking market and the rise in the market share of joint stock banks. In the period between 1996 and 2006, the number of branches opened by joint stock banks nationally increased from 17,337 to 24,618 (+41%), those of foreign banks from 75 to 128 (+70%). Instead branches of cooperative banks rose only from 6,981 to 7,592 (+8%). Their share on total branches declined from 40% in 1996 to 30% in 2006. The rise in the number of branches came along an expansion of banks' balance sheets: as banking assets rose substantially in total from 671.4 billion euros in 1990 to 2371.9 in 2004, according to Fiorentino et al. (2009).

Appendix B. Sample construction

Our analysis is based on the population of Italian manufacturing joint stock companies between 2007 and 2017 provided by Cerved from *Centrali dei Bilanci*. For each firm we have information on balance sheets. The total number of observations (firm*year) in the data for these years is 519,037. When we construct our measure of distance however, our sample is reduced to 453,374 observations, because firms' geographic coordinates are missing for some firms and therefore, we cannot compute their distance from the closest airport (the share of companies with no distance information does not change over time, being on average across years 12.6% and 12.5% in both 2007 and 2017). After these cleaning steps that include dropping firms with negative leverage values, we have 328,207 observations. This includes an average of 29,837 firm-observations per year varying between 26,892 in 2007 and 31,972 in 2017. In the table below we report the t-test on the regional and sector distribution between the initial and final samples: results show there are no significant differences across the two samples (Table B1).

We report firm distribution on the Italian territory using Italian provinces. Using these geographical entities, we can study the level of dispersion of leader firms in the Italian territory. In Figure B1 we report the geographical distribution of firms across Italian provinces where in each unit we report the share of firms (p) in each year t, 2007 or 2017, ($\frac{firms_{p,t}}{firms_t}$). The darkest areas are those with the highest share of firms.

Table B1. T-test on the regional and sector distribution

	Initial sample	Sample of analysis	T-stat of the difference	P-value
Panel A: Regional distribution				
Abruzzo	0.016	0.006	38.06	0.0000
Basilicata	0.003	0.001	14.78	0.0000
Calabria	0.005	0.001	24.26	0.0000
Campania	0.045	0.043	6.26	0.0000
Emilia Romagna	0.118	0.135	-23.21	0.0000
Friuli Venezia Giulia	0.025	0.027	-7.04	0.0000
Lazio	0.038	0.039	-2.99	0.0028
Liguria	0.011	0.003	39.37	0.0000
Lombardia	0.289	0.314	-24.76	0.0000
Marche	0.043	0.034	20.64	0.0000
Molise	0.001	0.000	13.94	0.0000
Piemonte	0.081	0.065	27.17	0.0000
Puglia	0.029	0.021	23.45	0.0000
Sardegna	0.007	0.000	48.47	0.0000
Sicilia	0.019	0.015	11.63	0.0000
Toscana	0.082	0.081	0.25	0.7952
Trentino Alto Adige	0.013	0.013	-0.75	0.4502
Umbria	0.012	0.010	8.83	0.0000
Valle D'Aosta	0.001	0.000	10.24	0.0000
Veneto	0.151	0.179	-33.74	0.0000
Panel B: 2-digit sector distribution				
10	0.079	0.077	4.19	0.0000
11	0.008	0.009	-2.39	0.0168
12	0.000	0.000	-0.31	0.7535
13	0.037	0.037	0.36	0.7170
14	0.038	0.037	2.71	0.0065
15	0.039	0.037	4.58	0.0000
16	0.025	0.023	7.18	0.0000
17	0.020	0.021	-4.20	0.0000
18	0.027	0.028	-2.40	0.0164
19	0.001	0.001	2.80	0.0050
20	0.029	0.033	-9.16	0.0000
21	0.005	0.007	-9.58	0.0000
22	0.057	0.059	-3.95	0.0001
23	0.050	0.045	11.26	0.0000
24	0.018	0.021	-9.69	0.0000
25	0.225	0.223	1.60	0.1081
26	0.027	0.029	-5.75	0.0000
27	0.037	0.038	-3.99	0.0001
28	0.129	0.137	-9.56	0.0000
29	0.016	0.017	-2.78	0.0054
30	0.012	0.012	1.73	0.0832
31	0.040	0.036	9.59	0.0000
32	0.029	0.029	1.50	0.1325
33	0.036	0.032	10.26	0.0000
Observations	519,037	328,207		

Note: Cerved data, 2007-2017, Authors' calculations

TFP estimation

The TFP of a firm is estimated using the residual of Cobb-Douglas value added production function, in the following model:

$$lny_{it} = \beta_0 + \beta_k lnk_{it} + \beta_l lnl_{it} + \omega_{it} + \epsilon_{it}$$

Where β_0 are the average value-added level across all firms and years, lny_{it} is the natural logarithm of the value added, lnk_{it} is the natural logarithm of capital input and lnl_{it} is the natural logarithm of labour input. Finally, ω_{it} is a productivity shock that could influence both capital and labour inputs and the whole production process while is just a ϵ_{it} random shock.

The TFP is therefore the following:

$$\widehat{\omega}_{it} = lny_{it} - \widehat{\beta_k} lnk_{it} - \widehat{\beta_l} lnl_{it}$$

We use two alternative methodologies to estimate the TFP. The first one suggested by Wooldridge (2009) where material inputs (used to proxy unobserved productivity shocks) are measured with consumption and general expenses from balance sheet data and labour is one year lagged. The reason why this control is necessary is due to the endogeneity of the capital and labour inputs that are likely to be linked to expectations on productivity levels and unobserved productivity shocks, that may drive both inputs and value-added simultaneously. Not controlling for unobserved productivity shocks biases the estimate as productivity is potentially correlated with the input choice. The second methodology is the Ackerberg et al. (2015) according to which intermediate inputs used to control for unobserved productivity should be also conditional on labour inputs.[36] We run a total of 24 regressions, separately for each manufacturing 2-digit sector (SIC codes 10 to 33) and we control for year fixed effects. In this way, we have a TFP distribution for each sector with comparable TFP measures across years. We also derive TFP measures corrected by firm and time varying markups measured as in De Loecker and Warzynski (2012). In Table B2 and B3 we report some statistics from these estimations. In Table B2 we show the mean, standard deviation and correlations across variables used to estimate the TFP. In Table B3 we show the coefficients for capital and labour for each methodology (Wooldridge and ACF).

[36] We also estimate the production function using a simple OLS and firm fixed effects estimation. Results are available upon request.

Table B2: Descriptive statistics and correlation coefficients of the variables that enter the estimation of the production function

	Mean	Std. Dev.	Min.	Max.	y_{it}	k_{it}	l_{it}	m_{it}	lc_{it}
y_{it}	13.744	1.075	9.950	21.644	1				
k_{it}	13.091	1.751	6.118	20.744	.695	1			
l_{it}	2.862	.899	1.609	7.806	.909	.629	1		
m_{it}	13.811	1.642	5.552	22.989	.760	.612	.670	1	
lc_{it}	13.353	1.018	9.420	18.851	.954	.645	.953	.707	1

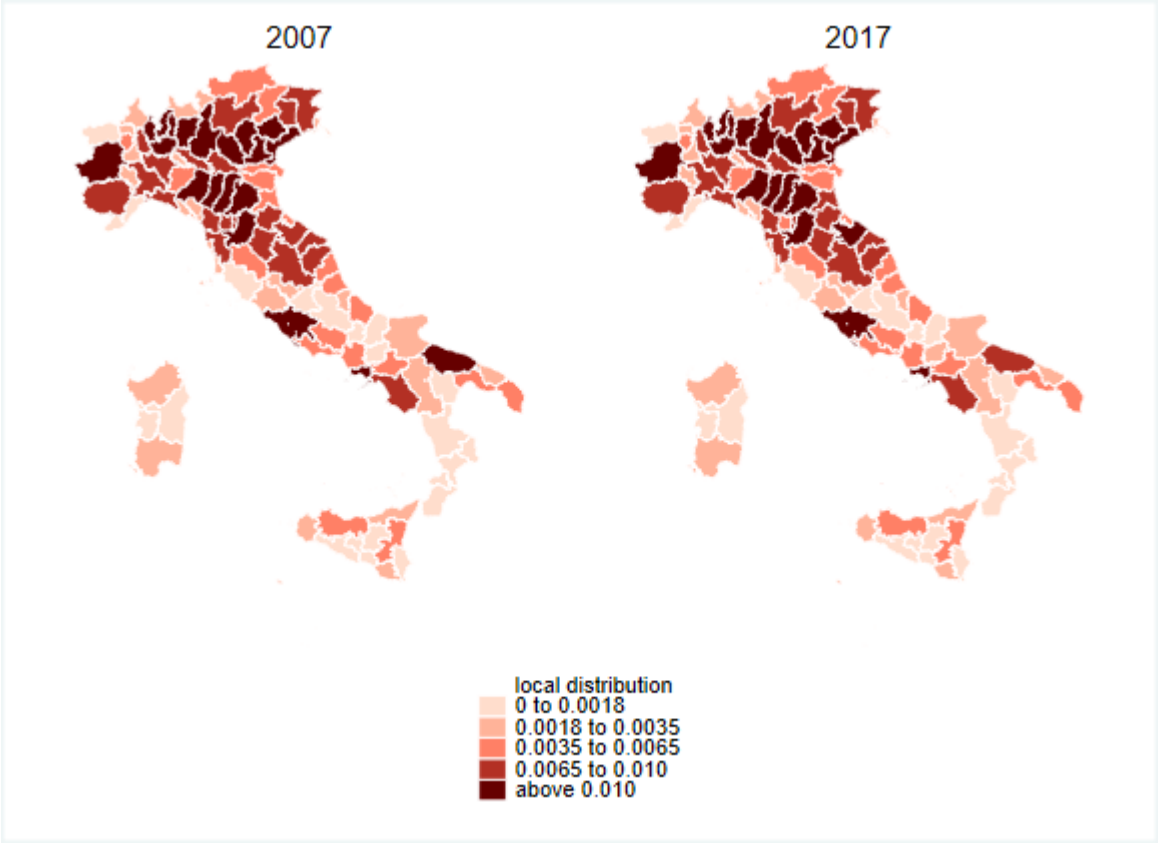
Notes: All variables are log-transformed. y_{it} denotes value added; k_{it} denotes the capital input; l_{it} denotes the labor input; m_{it} denotes intermediate inputs; lc_{it} denotes labour costs. Descriptive statistics and the correlation matrix refer to a sample of 71,068 firms, i.e. 519,037 observations over the period 2007-2017.

Table B3: Estimated inputs' elasticities of the production functions

Industry	W (2009)		ACF (2015) – no. of employees		No. of Observations
	k_{it}	l_{it}	k_{it}	l_{it}	
10	0.079****	0.708****	0.251****	0.867****	41,378
	(0.006)	(0.003)	(0.000)	(0.000)	
11	0.091****	0.744****	0.167****	0.969****	4,656
	(0.024)	(0.012)	(0.022)	(0.125)	
12	0.040	0.593****	0.295	0.749	41
	(0.025)	(0.053)	(0.376)	(1.098)	
13	0.050****	0.811****	0.072	0.922	19,571
	(0.006)	(0.004)	(/)	(/)	
14	0.065****	0.785****	0.139****	0.887****	20,172
	(0.006)	(0.004)	(0.000)	(0.000)	
15	0.072****	0.765****	0.150****	0.890****	20,641
	(0.006)	(0.004)	(0.000)	(0.000)	
16	0.043****	0.760****	0.116****	0.912****	13,413
	(0.007)	(0.004)	(0.000)	(0.000)	
17	0.049****	0.758****	0.130	0.924	10,543
	(0.008)	(0.005)	(/)	(/)	
18	0.028****	0.817****	0.119****	0.946	14,492
	(0.007)	(0.005)	(0.000)	(/)	
19	0.030	0.621****	0.264	0.867****	987
	(0.096)	(0.038)	(0.250)	(0.822)	
20	0.068****	0.739****	0.132****	0.910****	15,443
	(0.008)	(0.005)	(0.000)	(0.000)	
21	0.096***	0.638****	0.052****	0.979****	2,786
	(0.022)	(0.011)	(0.000)	(0.000)	
22	0.054****	0.769****	0.128	0.928	29,671
	(0.005)	(0.003)	(/)	(/)	
23	0.040****	0.742****	0.108****	0.910****	26,449
	(0.007)	(0.004)	(0.000)	(0.000)	
24	-0.007	0.788****	0.119****	0.880****	9,600
	(0.014)	(0.006)	(0.000)	(0.000)	
25	0.061****	0.840****	0.123	0.945	116,907
	(0.002)	(0.001)	(/)	(/)	
26	0.045****	0.819****	0.057****	0.965****	14,342
	(0.007)	(0.005)	(0.000)	(0.000)	
27	0.054****	0.760****	0.083	0.945	19,324
	(0.006)	(0.004)	(/)	(/)	
28	0.048****	0.783****	0.068	0.986	67,449
	(0.009)	(0.002)	(/)	(/)	
29	0.071****	0.758****	0.094****	0.934****	8,624
	(0.010)	(0.006)	(0.000)	(0.000)	
30	0.070****	0.838****	0.091****	0.902****	6,614
	(0.010)	(0.006)	(0.013)	(0.130)	
31	0.059****	0.737****	0.075****	0.928	21,253
	(0.005)	(0.004)	(0.000)	(/)	
32	0.075****	0.816****	0.105****	0.931****	15,496
	(0.009)	(0.004)	(0.000)	(0.000)	
33	0.038****	0.873****	0.093****	0.917****	19,185
	(0.005)	(0.004)	(0.000)	(0.000)	

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; **** $p < 0.001$. *W denotes Wooldridge's (2009) approach, while ACF denotes Ackerberg et al.'s (2015) approach to firms' TFP estimation.* k_{it} *denotes the capital input,* l_{it} *denotes the number of employees as labour input. TFP is estimated on a sample of 71,068 firms, i.e. 519,037 observations over the period 2007-2017. Standard errors are shown in parentheses.*

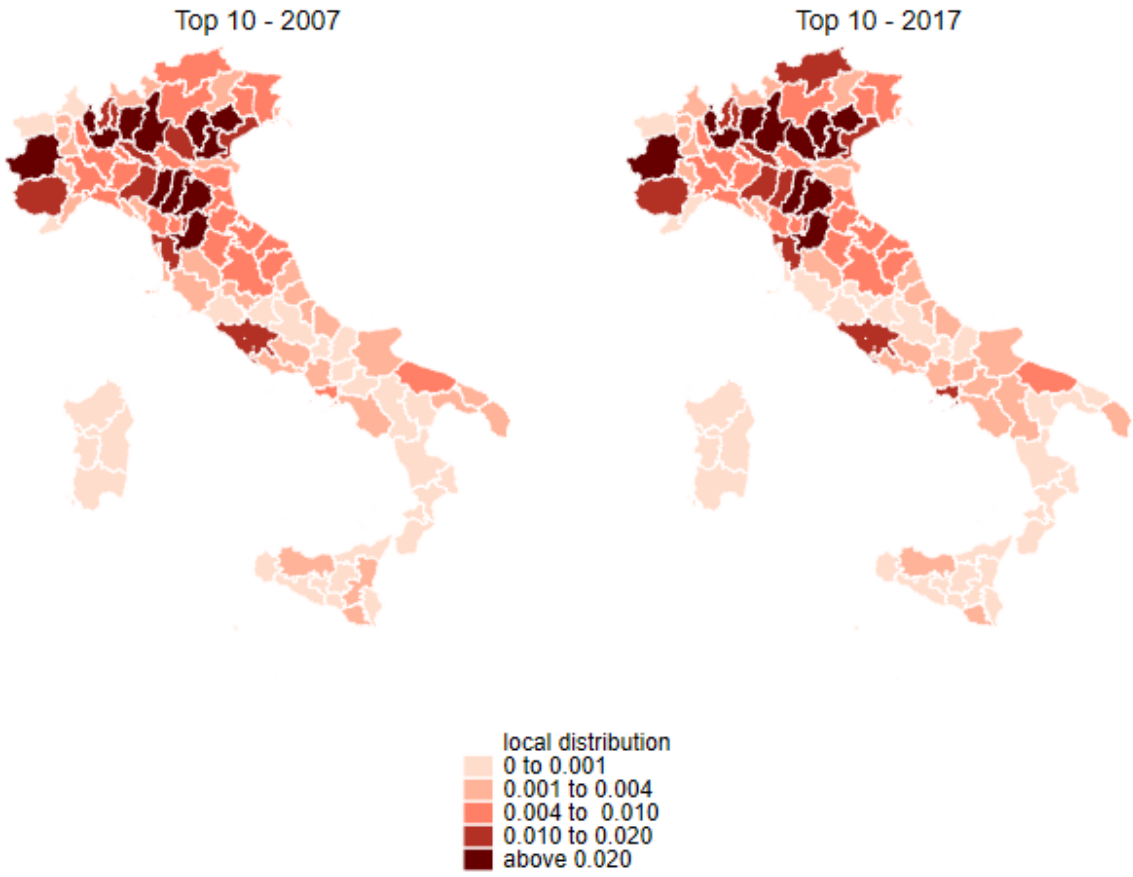
Figure B1. Share of firms by province



Note: Share of firms by province. The unit of analysis is provinces, and in each unit we report the share of firms in that province over the total firms in Italy, in 2007 and in 2017 separately.

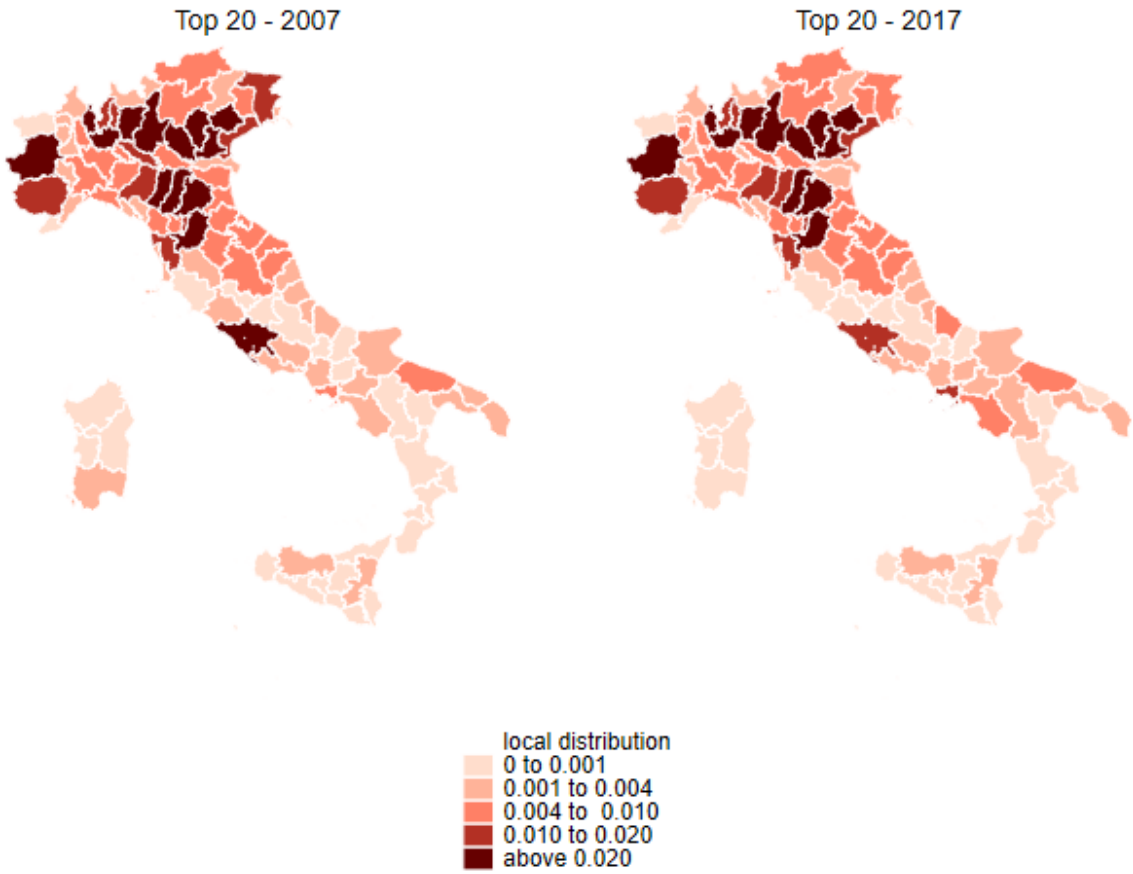
Appendix C. Other tables and figures

Figure C1. Distribution of leaders across provinces – Top 10



Note: Leaders' distribution across provinces. The unit of analysis is the province, and in each unit we report the share of leaders in that province over the total leaders in Italy, in 2007 and in 2017 separately. Leaders defined using the same methodology as Andrews et al (2015), where the number of firms is constant across years and defined as the median number of firms above the 90th percentile. TFP defined using the ACF (2015) method.

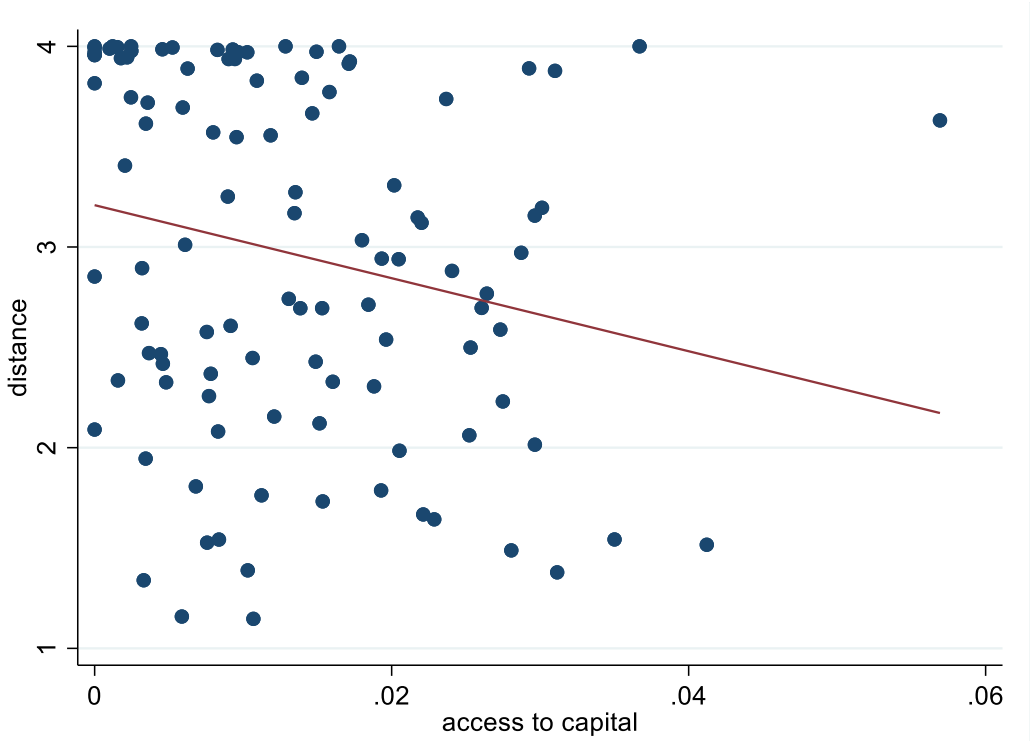
Figure C2. Distribution of leaders across provinces – Top 20



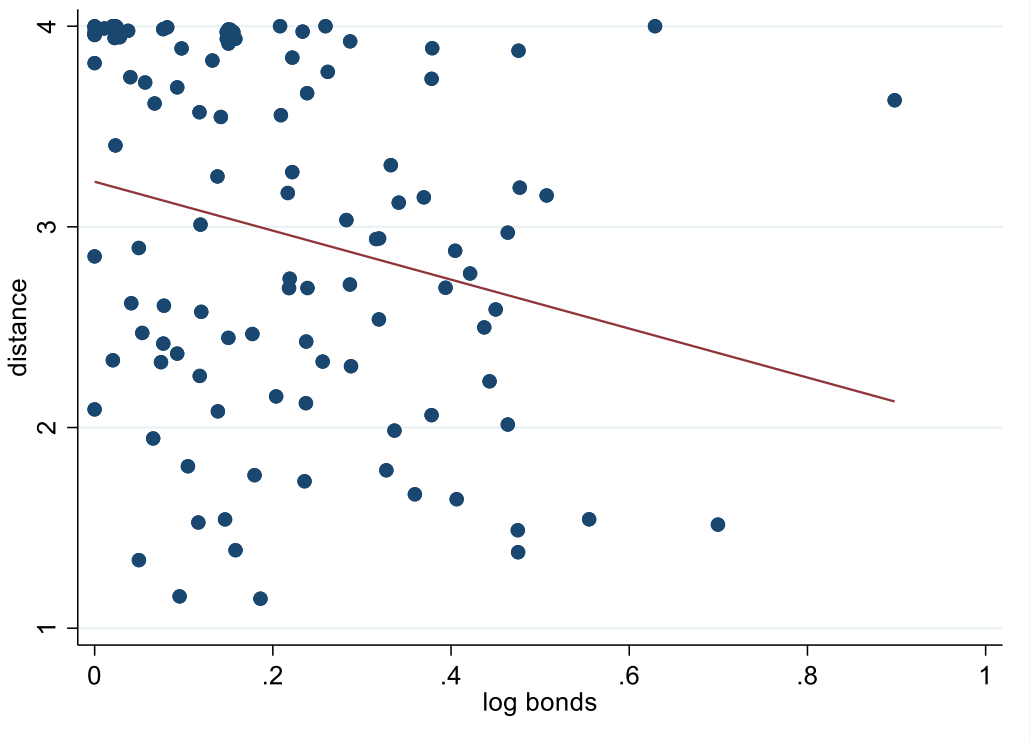
Note: Leaders' distribution across provinces. The unit of analysis is the province, and in each unit we report the share of leaders in that province over the total leaders in Italy, in 2007 and in 2017 separately. Leaders defined using the same methodology as Andrews et al (2015), where the number of firms is constant across years and defined as the median number of firms above the 80th percentile. TFP defined using the ACF (2015) method.

Figure C3: Scatterplots between access to capital markets/log bonds and distance

Panel A



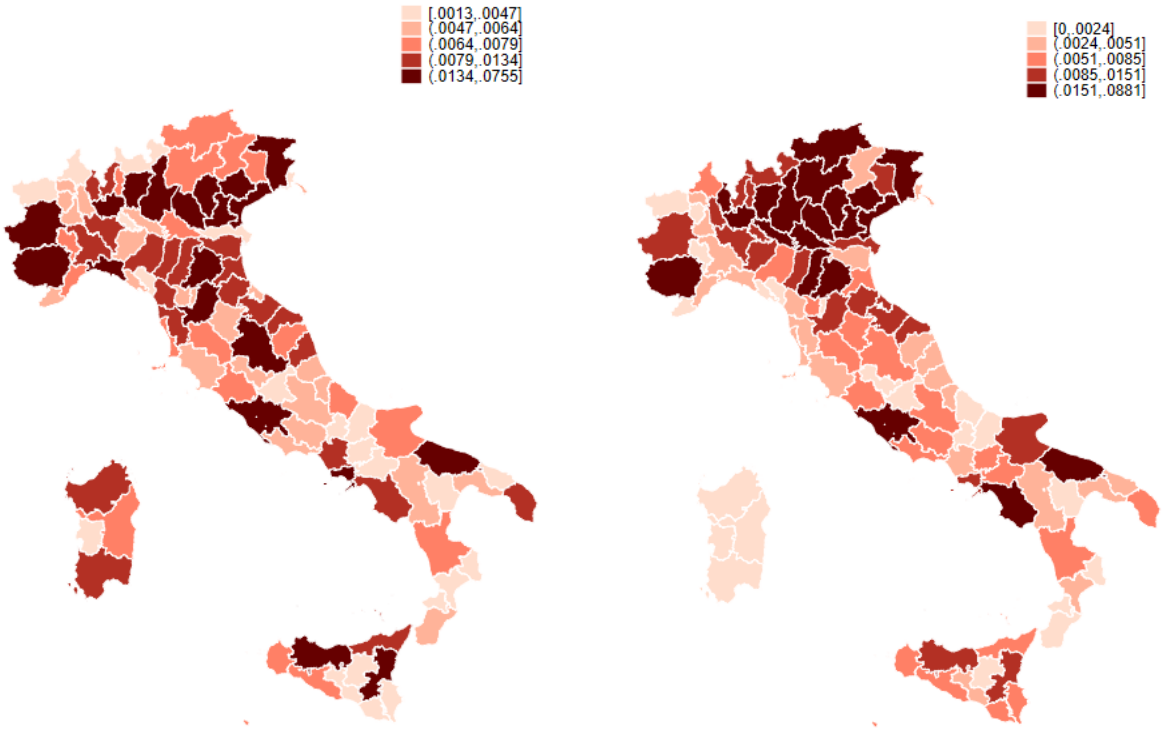
Panel B



Note: We report the average distance (y-axis) and the share of firms with capital market access (Panel A) or average of log bonds (x-axis), by province and year.

Figure C4: Initial distribution of different types of branches

A. Joint Stock branches **B. Mutual branches**



Note: Share of type of branches by province. The unit of analysis is province, and in each unit we report the share of type of branches in that province over the total branches in Italy averaged over the period 1996-1998.

Figure C5. Location of airports

Table C1. Descriptive statistics

Variable	Description	Mean	Std.Dev.	Obs
TFP	Estimated from a value-added based production function where inputs are the number of employees and real capital	9.60	0.69	328,207
TFP (net markup)	TFP corrected by time varying markups	9.50	0.59	328,207
Probability to be leaders (top 5)	Dummy equal to 1 if the firm is at or above the 95th percentile of the TFP distribution in each year and 2-digit sector	0.06	0.23	328,207
Probability to be leaders (top 10)	Dummy equal to 1 if the firm is at or above the 90th percentile of the TFP distribution in each year and 2-digit sector	0.11	0.31	328,207
Probability to be leaders (top 20)	Dummy equal to 1 if the firm is at or above the 80th percentile of the TFP distribution in each year and 2-digit sector	0.22	0.41	328,207
Bank debt	Debt to banks	1,745,061	7,061,240	328,207
Log (bank debt)	Log of debt to banks	10.73	5.33	328,207
Total bonds	Sum of convertible and non-convertible bonds	54,267	1,249,079	328,207
Log (total bonds)	Log of convertible and non-convertible bonds	0.33	2.12	328,207
Access to capital markets (dummy)	Dummy equal to 1 if the firm has a positive value of bonds in its balance sheet, 0 otherwise	0.02	0.15	328,207
Average Total Debts	Total debt	4,958,187	18,465,244	328,207
ΔSimulBranches mutual	Nationwide yearly growth of mutual branches with respect to 2007 distributed at the provincial level 10 years before the firm's productivity observed, according to the average share of mutual branches in each province in 1996-1998	-0.00008	0.00260	328,207
ΔSimulBranches joint stock	Nationwide yearly growth of joint stock branches with respect to 2007 distributed at the provincial level 10 years before the firm's productivity observed, according to the average share of joint stock branches in each province in 1996-1998	0.00103	0.00134	328,207
Distance	Firms' distance from local airports weighted by the number of passengers in 2007	24.74	16.67	328,207
Initial size	Number of employees in 2007	30.16	55.02	328,207
Mean of initial sales growth rates	Average sales growth rates of a firm in the first three observed consecutive years before the 2007	51,473	6,719,818	325,036
Age	Age of a firm	21.68	14.61	319,439
Log (initial R&D expenditures)	Log of R&D expenditures in 2007	1.78	3.69	328,207
Value added	Value added per capital at the regional level	28,119	4,773	328,207
Employment rates	Employment rates at the regional level among people between 20 and 64 years old	67.43	6.98	328,207
Share of graduates	Share of people with tertiary education at the regional level among those that are between 25 and 64 years old	0.16	0.03	328,207

Note: Cerved data, 2007-2017, Authors' calculation

Table C2. Access to capital markets and firm performance- First stage

	(1)	(2)	(3)	(4)	(5)	(6)
	Log (total bonds)			Access to capital (dummy)		
ΔSimulBranches mutual	19.170**	17.258***	9.611***	1.322**	1.191***	0.651***
	(7.678)	(6.176)	(3.463)	(0.556)	(0.452)	(0.247)
ΔSimulBranches joint stock	63.476**	51.128**	25.996**	4.437**	3.570**	1.822**
	(31.357)	(24.545)	(10.586)	(2.246)	(1.772)	(0.735)
Distance	0.002*	0.001		0.000*	0.000	
	(0.001)	(0.001)		(0.000)	(0.000)	
ΔSimulBranches mutual*Distance	-0.678	-0.579*	-0.283**	-0.047	-0.040	-0.020**
	(0.446)	(0.346)	(0.140)	(0.032)	(0.025)	(0.010)
ΔSimulBranches joint stock*Distance	-3.378*	-2.280	-0.808*	-0.237*	-0.160	-0.061**
	(1.923)	(1.394)	(0.431)	(0.137)	(0.101)	(0.030)
Firm level controls	no	yes	no	no	yes	no
Regional level controls	no	yes	yes	no	yes	yes
Province fixed effects	yes	yes	no	yes	yes	no
Industry X year fixed effects	yes	yes	yes	yes	yes	yes
Firm fixed effects	no	no	yes	no	no	yes
Observations	328,207	316,284	321,892	328,207	316,284	321,892
KP Wald F-statistic	6.496	7.636	2.083	5.612	6.029	1.788

*Note: Cerved data 2007-2017, Authors' calculations. Standard errors clustered at provincial level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Firm level controls: size at the beginning of the period, average sales growth rates in the first three years observed, age of a firm, and log of initial R&D expenditures. Regional level controls: value added per capita, share of people with tertiary education and employment rates.*

Table C3. Access to capital markets and firm performance (by size) – firm fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	less than 10 empl		10 to 49 empl		50 to 249 empl		250 or more empl	
	Panel A: log bonds							
Dependent: TFP (net markup)								
Log (total bonds)	-0.002	-0.115	-0.001*	-0.007	-0.001**	0.053	0.000	-0.122
	(0.002)	(0.158)	(0.001)	(0.044)	(0.000)	(0.033)	(0.001)	(0.339)
Dependent: Probability to be leaders (top 5)								
Log (total bonds)	-0.000	-0.007	-0.000	0.039	-0.000	0.022	0.001	0.116
	(0.002)	(0.120)	(0.001)	(0.062)	(0.001)	(0.021)	(0.001)	(0.410)
Dependent: Probability to be leaders (top 10)								
Log (total bonds)	-0.000	0.017	0.000	0.027	-0.000	0.004	-0.000	0.085
	(0.003)	(0.157)	(0.001)	(0.099)	(0.001)	(0.038)	(0.001)	(0.303)
Dependent: Probability to be leaders (top 20)								
Log (total bonds)	0.004	-0.009	-0.000	0.130	-0.000	0.033	0.002	0.370
	(0.004)	(0.215)	(0.001)	(0.136)	(0.001)	(0.084)	(0.004)	(1.359)
KP Wald F-statistic		4.676		3.037		1.549		0.084
	Panel B: Access to capital markets							
Dependent: TFP (net markup)								
Access to capital (dummy)	-0.020	-1.826	-0.010	-0.167	-0.013**	0.827	0.008	0.452
	(0.023)	(2.041)	(0.007)	(0.628)	(0.006)	(0.559)	(0.016)	(1.891)
Dependent: Probability to be leaders (top 5)								
Access to capital (dummy)	0.005	0.179	-0.004	0.568	-0.003	0.335	0.013*	0.101
	(0.018)	(1.365)	(0.009)	(0.878)	(0.007)	(0.342)	(0.008)	(1.624)
Dependent: Probability to be leaders (top 10)								
Access to capital (dummy)	0.003	0.769	0.005	0.335	-0.002	0.051	-0.002	2.777
	(0.035)	(1.748)	(0.011)	(1.405)	(0.009)	(0.587)	(0.015)	(6.806)
Dependent: Probability to be leaders (top 20)								
Access to capital (dummy)	0.071*	0.222	-0.005	1.808	-0.006	0.498	0.024	9.628
	(0.040)	(2.584)	(0.012)	(1.939)	(0.010)	(1.316)	(0.056)	(29.221)
KP Wald F-statistic		4.826		2.789		1.427		0.051
Firm level controls	no	no	no	no	no	no	no	no
Regional level controls	yes	yes	yes	yes	yes	yes	yes	yes
Province fixed effects	no	no	no	no	no	no	no	no
Industry X year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Firm fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Observations	104,012	104,012	170,129	170,129	44,780	44,780	2,749	2,749

*Note: Cerved data 2007-2017, Authors' calculations. Standard errors clustered at provincial level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Regional level controls: value added per capita, share of people with tertiary education and employment rates.*

Table C4. Access to capital markets and firm performance (Wooldridge)

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
			Panel A: log bonds			
Dependent: TFP (net markup)						
Log (total bonds)	0.014***	0.215***	0.003***	0.222***	-0.001	0.069*
	(0.001)	(0.053)	(0.001)	(0.074)	(0.000)	(0.036)
Dependent: Probability to be leaders (top 5)						
Log (total bonds)	0.006***	0.151***	0.003***	0.177***	0.001**	0.044
	(0.001)	(0.022)	(0.001)	(0.040)	(0.000)	(0.076)
Dependent: Probability to be leaders (top 10)						
Log (total bonds)	0.011***	0.219***	0.006***	0.239***	0.001**	0.147
	(0.001)	(0.034)	(0.001)	(0.064)	(0.001)	(0.122)
Dependent: Probability to be leaders (top 20)						
Log (total bonds)	0.017***	0.319***	0.009***	0.345***	0.001	0.149
	(0.001)	(0.049)	(0.001)	(0.082)	(0.001)	(0.096)
KP Wald F-statistic		6.496		7.636		2.083
			Panel B: Access to capital markets			
Dependent: TFP (net markup)						
Access to capital (dummy)	0.180***	3.023***	0.043***	3.111***	-0.007	0.907*
	(0.009)	(0.767)	(0.008)	(1.067)	(0.005)	(0.531)
Dependent: Probability to be leaders (top 5)						
Access to capital (dummy)	0.072***	2.153***	0.035***	2.541***	0.015**	0.613
	(0.009)	(0.323)	(0.009)	(0.607)	(0.007)	(1.123)
Dependent: Probability to be leaders (top 10)						
Access to capital (dummy)	0.144***	3.121***	0.073***	3.430***	0.017**	2.132
	(0.012)	(0.503)	(0.012)	(0.969)	(0.007)	(1.828)
Dependent: Probability to be leaders (top 20)						
Access to capital (dummy)	0.225***	4.551***	0.111***	4.948***	0.016*	2.160
	(0.014)	(0.714)	(0.013)	(1.249)	(0.009)	(1.444)
KP Wald F-statistic		5.612		6.029		1.788
Firm level controls	no	no	yes	yes	no	no
Regional level controls	no	no	yes	yes	yes	yes
Province fixed effects	yes	yes	yes	yes	no	no
Industry X year fixed effects	yes	yes	yes	yes	yes	yes
Firm fixed effects	no	no	no	no	yes	yes
Observations	328,207	328,207	316,284	316,284	321,892	321,892

*Note: Cerved data 2007-2017, Authors' calculations. Standard errors clustered at provincial level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Firm level controls: size at the beginning of the period, average sales growth rates in the first three years observed, age of a firm, and log of initial R&D expenditures. Regional level controls: value added per capita, share of people with tertiary education and employment rates.*

Table C5. Access to capital markets and firm performance (ACF using labour costs)

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
			Panel A: log bonds			
Dependent: TFP (net markup)						
Log (total bonds)	-0.002***	0.022*	-0.002***	0.043**	-0.000***	0.023
	(0.000)	(0.013)	(0.000)	(0.018)	(0.000)	(0.014)
Dependent: Probability to be leaders (top 5)						
Log (total bonds)	0.001***	0.033*	0.002***	0.039*	0.000	0.033
	(0.000)	(0.018)	(0.001)	(0.021)	(0.000)	(0.056)
Dependent: Probability to be leaders (top 10)						
Log (total bonds)	0.003***	0.083***	0.003***	0.094**	0.001**	0.025
	(0.001)	(0.027)	(0.001)	(0.037)	(0.001)	(0.084)
Dependent: Probability to be leaders (top 20)						
Log (total bonds)	0.004***	0.138***	0.004***	0.167***	0.001*	0.035
	(0.001)	(0.033)	(0.001)	(0.047)	(0.001)	(0.113)
KP Wald F-statistic		6.496		7.636		2.083
			Panel B: Access to capital markets			
Dependent: TFP (net markup)						
Access to capital (dummy)	-0.029***	0.313*	-0.024***	0.607**	-0.005***	0.341
	(0.004)	(0.182)	(0.004)	(0.266)	(0.001)	(0.218)
Dependent: Probability to be leaders (top 5)						
Access to capital (dummy)	0.017**	0.475*	0.021***	0.569*	0.001	0.461
	(0.007)	(0.254)	(0.007)	(0.299)	(0.005)	(0.833)
Dependent: Probability to be leaders (top 10)						
Access to capital (dummy)	0.031***	1.189***	0.034***	1.376**	0.015**	0.457
	(0.009)	(0.389)	(0.009)	(0.545)	(0.007)	(1.272)
Dependent: Probability to be leaders (top 20)						
Access to capital (dummy)	0.051***	1.980***	0.052***	2.426***	0.016**	0.618
	(0.012)	(0.473)	(0.012)	(0.668)	(0.008)	(1.712)
KP Wald F-statistic		5.612		6.029		1.788
Firm level controls	no	no	yes	yes	no	no
Regional level controls	no	no	yes	yes	yes	yes
Province fixed effects	yes	yes	yes	yes	no	no
Industry X year fixed effects	yes	yes	yes	yes	yes	yes
Firm fixed effects	no	no	no	no	yes	yes
Observations	328,207	328,207	316,284	316,284	321,892	321,892

*Note: Cerved data 2007-2017, Authors' calculations. Standard errors clustered at provincial level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Firm level controls: size at the beginning of the period, average sales growth rates in the first three years observed, age of a firm, and log of initial R&D expenditures. Regional level controls: value added per capita, share of people with tertiary education and employment rates.*

Table C6. Asinh bonds and firm performance

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
	Panel A: Asinh bonds					
Dependent: TFP (net markup)						
Asinh total bonds	-0.004***	0.089*	-0.004***	0.196*	-0.002***	0.037
	(0.000)	(0.053)	(0.000)	(0.102)	(0.000)	(0.031)
Dependent: Probability to be leaders (top 5)						
Asinh log (total bonds)	-0.001	0.097***	-0.000	0.143***	-0.000	0.068
	(0.000)	(0.018)	(0.000)	(0.037)	(0.000)	(0.055)
Dependent: Probability to be leaders (top 10)						
Asinh log (total bonds)	-0.000	0.175***	0.000	0.248***	-0.000	0.071
	(0.001)	(0.036)	(0.001)	(0.062)	(0.000)	(0.089)
Dependent: Probability to be leaders (top 20)						
Asinh log (total bonds)	0.000	0.202***	0.000	0.317***	-0.001	0.123
	(0.001)	(0.053)	(0.001)	(0.099)	(0.001)	(0.148)
KP Wald F-statistic		6.463		7.570		2.069
Firm level controls	no	no	yes	yes	no	no
Regional level controls	no	no	yes	yes	yes	yes
Province fixed effects	yes	yes	yes	yes	no	no
Industry X year fixed effects	yes	yes	yes	yes	yes	yes
Firm fixed effects	no	no	no	no	yes	yes
Observations	328,207	328,207	316,284	316,284	321,892	321,892

Note: Cerved data 2007-2017, Authors' calculations. asinh is the inverse hyperbolic sine defined as $\log[bonds + \sqrt{bonds^2 + 1}$. *Standard errors clustered at provincial level in parentheses, ***p<0.01, **p<0.05, *p<0.1. Firm level controls: size at the beginning of the period, average sales growth rates in the first three years observed, age of a firm, and log of initial R&D expenditures. Regional level controls: value added per capita, share of people with tertiary education and employment rates.*

Table C7. Access to capital markets and firm performance - lagged log of bank debt

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
	Panel A: log bonds					
Dependent: TFP (net markup)						
Log (total bonds)	-0.003***	0.122*	-0.003***	0.226	-0.002***	0.021
	(0.000)	(0.068)	(0.000)	(0.138)	(0.000)	(0.025)
Dependent: Probability to be leaders (top 5)						
Log (total bonds)	-0.000	0.094***	-0.000	0.118***	-0.000	0.064
	(0.000)	(0.018)	(0.000)	(0.028)	(0.000)	(0.061)
Dependent: Probability to be leaders (top 10)						
Log (total bonds)	0.001	0.164***	0.000	0.203***	-0.001	0.065
	(0.001)	(0.037)	(0.001)	(0.051)	(0.001)	(0.088)
Dependent: Probability to be leaders (top 20)						
Log (total bonds)	0.001	0.201***	0.001	0.284***	-0.001**	0.135
	(0.001)	(0.064)	(0.001)	(0.102)	(0.001)	(0.136)
KP Wald F-statistic		6.190		6.999		2.912
	Panel B: Access to capital markets					
Dependent: TFP (net markup)						
Access to capital (dummy)	-0.045***	1.675*	-0.047***	3.120	2.617	2.617
	(0.006)	(0.940)	(0.006)	(1.946)	2.617	2.617
Dependent: Probability to be leaders (top 5)						
Access to capital (dummy)	-0.003	1.331***	-0.004	1.698***	-0.004	0.908
	(0.006)	(0.259)	(0.006)	(0.419)	(0.006)	(0.865)
Dependent: Probability to be leaders (top 10)						
Access to capital (dummy)	0.004	2.336***	0.002	2.924***	-0.010	0.952
	(0.010)	(0.545)	(0.010)	(0.767)	(0.008)	(1.252)
Dependent: Probability to be leaders (top 20)						
Access to capital (dummy)	0.011	2.842***	0.008	4.055***	-0.018*	1.965
	(0.012)	(0.924)	(0.012)	(1.515)	(0.009)	(1.953)
KP Wald F-statistic		4.791		5.147		2.617
Firm level controls	no	no	yes	yes	no	no
Regional level controls	no	no	yes	yes	yes	yes
Province fixed effects	yes	yes	yes	yes	no	no
Industry X year fixed effects	yes	yes	yes	yes	yes	yes
Firm fixed effects	no	no	no	no	yes	yes
Observations	253,842	253,842	244,550	244,550	248,172	248,172

*Note: Cerved data 2007-2017, Authors' calculations. Standard errors clustered at provincial level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Firm level controls: size at the beginning of the period, average sales growth rates in the first three years observed, age of a firm, log of initial R&D expenditures and 1 year lagged log of debt. Regional level controls: value added per capita, share of people with tertiary education and employment rates. We control for lagged log value of debt to banks in all regressions.*

Table C8. Access to capital markets and firm performance - balanced panel

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
	Panel A: log bonds					
Dependent: TFP (net markup)						
Log (total bonds)	-0.003***	0.057	-0.003***	0.217	-0.002***	0.038*
	(0.001)	(0.055)	(0.001)	(0.211)	(0.001)	(0.023)
Dependent: Probability to be leaders (top 5)						
Log (total bonds)	-0.002***	0.068**	-0.001*	0.132*	-0.001	0.082
	(0.001)	(0.026)	(0.001)	(0.073)	(0.001)	(0.053)
Dependent: Probability to be leaders (top 10)						
Log (total bonds)	-0.002*	0.101**	-0.001	0.181*	-0.000	0.063
	(0.001)	(0.039)	(0.001)	(0.098)	(0.001)	(0.067)
Dependent: Probability to be leaders (top 20)						
Log (total bonds)	-0.002	0.104*	-0.001	0.240	-0.001	0.142*
	(0.001)	(0.057)	(0.002)	(0.165)	(0.001)	(0.077)
KP Wald F-statistic		2.493		1.520		2.313
	Panel B: Access to capital markets					
Dependent: TFP (net markup)						
Access to capital (dummy)	-0.048***	0.669	-0.044***	2.907	-0.027***	0.525
	(0.010)	(0.729)	(0.010)	(2.875)	(0.007)	(0.321)
Dependent: Probability to be leaders (top 5)						
Access to capital (dummy)	-0.026***	0.958**	-0.020**	1.940*	-0.008	1.164
	(0.008)	(0.372)	(0.010)	(1.102)	(0.007)	(0.746)
Dependent: Probability to be leaders (top 10)						
Access to capital (dummy)	-0.029*	1.418**	-0.019	2.640*	-0.003	0.859
	(0.016)	(0.555)	(0.018)	(1.495)	(0.011)	(0.940)
Dependent: Probability to be leaders (top 20)						
Access to capital (dummy)	-0.029	1.448*	-0.014	3.519	-0.008	2.038*
	(0.019)	(0.805)	(0.021)	(2.455)	(0.010)	(1.155)
KP Wald F-statistic		2.165		1.228		2.424
Firm level controls	no	no	yes	yes	no	no
Regional level controls	no	no	yes	yes	yes	yes
Province fixed effects	yes	yes	yes	yes	no	no
Industry X year fixed effects	yes	yes	yes	yes	yes	yes
Firm fixed effects	no	no	no	no	yes	yes
Observations	107,030	107,030	102,718	102,718	107,030	107,030

*Note: Cerved data 2007-2017, Authors' calculations. Standard errors clustered at provincial level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Firm level controls: size at the beginning of the period, average sales growth rates in the first three years observed, age of a firm, and log of initial R&D expenditures. Regional level controls: value added per capita, share of people with tertiary education and employment rates.*