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To my parents and my wife. For their love, patience, encouragement, and endless support.

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ABSTRACT

In this dissertation, I combine two papers that study the extent and implications of resource misallocation across firms. In the first chapter, written with Francesco Manaresi, we rely on first principles of economic theory to measure capital and labor misallocation at the firm level. Using a novel micro-database on firm-specific borrowing costs and wages, we demonstrate that distortions in firms' employment and investment policies can be empirically measured using firm-level gaps between marginal revenue products and user costs (MRP-cost gaps). We estimate MRP-cost gaps for 4 million firm-year observations in Italy between 1997 and 2013, showing that the variation in these measures is closely related to the extent of credit market frictions and to the degree of labor market rigidities individual firms face. Using the estimated MRP-cost gaps, we propose a reallocation algorithm that helps us assess the scope of capital and labor misallocation in Italy, and its impact on aggregate output and total factor productivity (TFP). We calculate that holding constant the aggregate capital and labor endowments in the economy, the Italian corporate sector could produce between 3% to 4% more output by reallocating resources from over-endowed producers to higher-value users. The output losses from misallocation are larger during episodes of macro-financial instability, in non-manufacturing industries, and in geographical regions with less developed socio-economic institutions.

In the second chapter, I focus on the fundamental role played by financial intermediaries in enhancing economic growth, lending to firms and households and reallocating capital to the highest-value use. In this paper, joint work with Margherita Bottero and Filippo Mezzanotti, we study the role played by banks' security portfolio in the propagation of macro-financial shocks originated outside national borders. We document that swings in the price and riskiness of securities assets may lead to adjustments in banks' credit supply, with potential adverse effects on the real economy. In particular, in the context of the

European crisis, we show that the shock to the banks' sovereign portfolio caused by the 2010 Greek bailout was passed on to Italian firms through a credit contraction. This was particularly the case for banks with a weaker balance sheet. The contraction in credit was similar for both large and small firms, but it only negatively affected the investment and employment decisions of smaller firms.

CHAPTER 1

DO MARGINAL PRODUCTS DIFFER FROM USER COSTS? MICRO-LEVEL EVIDENCE FROM ITALIAN FIRMS

Simone Lenzu† and Francesco Manaresi‡[1]

1.1 Introduction

Research in economics and finance has long been interested in measuring the extent and implications of resource misallocation.[2] An intuitive way to conceptualize misallocation is to think of frictions and regulations as implicit taxes that generate wedges in the first-order conditions characterizing firms' optimal investment and employment policies ([4]; [5]). This approach captures the idea that producers may face differential relative costs when they try to acquire capital and labor inputs in the market, either because they are charged different prices or because they face quantity constraints (shadow prices). When differential costs do not reflect heterogeneity in fundamentals or risk, they cause some producers to be either too large or too small relative to their "socially efficient" size. This misallo-

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2. See [1], [2], [3], and the literature cited.

cation squanders scarce resources, reducing aggregate total factor productivity (TFP), and ultimately impairing economic growth ([6]).

Despite the large interest in this topic, data limitations have prevented researchers from directly measuring deviations from optimal capital and labor policies, mostly due of the inability to gather micro-data on the user costs of capital and labor paid by individual producers. To overcome these empirical constraints, the literature has produced appealing indirect measures of misallocation (e.g., [1]) that, however, rely on specific assumptions about firms' demand and production technologies and therefore might over- or understate the extent of misallocation when these assumptions are violated ([7]; [8]).

In this paper, we shed light on the distribution of the firm-level gap between marginal revenue products of capital and labor and their user costs (MRP-cost gaps), provide evidence of the relation of such gaps to market frictions and regulations, and ultimately use them to quantify the impact of resource misallocation on aggregate TPF and output. We assemble a comprehensive bank-firm-employee matched panel database that contains micro-level information on firm-specific wages, borrowing costs, balance-sheet data, and bank credit for the sample of non-financial corporations active in Italy between 1997 and 2013. We link accounting variables from the census of corporations to the archives of the National Credit Register and to employer-employee records obtained from the social security administration. The coverage, granularity, and richness of our data puts us in the unique position of observing the distribution of the user cost of both capital and labor, and allows us to estimate the distribution of marginal revenue products of primary inputs ([9]; [10]).

To gain intuition on the economic content of MRP-cost gaps, let us consider a neoclassical environment with homogeneous producers and no risk. When input policies are fully unconstrained, firms accumulate assets and hire labor up to the point where their marginal revenue products are equal to their user costs. We show that this intuition can be generalized to a more realistic framework with heterogeneous producers, where capital structure matters and default risk is endogenous. In particular, when debt is the marginal source of financing and borrowing rates are pre-determined and rigid, the gap between the marginal revenue product of capital and its user cost (the sum of the interest rate and the depreciation rate on the capital stock) is positively related to the shadow cost of capital that is generated by binding credit constraints ([11,12]). Similarly, when wages are rigid, the gap between the marginal revenue product of labor (MRPL) and the wage is proportional to the implicit cost of labor that firms face, such as the ones generated by regulatory interventions in labor markets ([13]).

Our research has three primary empirical results. First, we characterize the distributions of MRP-cost gaps of capital and labor. According to our metric, the central percentiles of the distributions are occupied by firms whose capital and labor endowment appears to be relatively undistorted. The median gaps of capital and labor are 3.5 % and 6 thousand euros for capital and labor, respectively. We calculate that, to close the gaps of the median firm, investing an amount of capital worth 1% of firm assets and hire 3% extra workers would be sufficient.

Yet the distributions of MRP-cost gaps are dispersed and highly right-skewed. The average capital and labor gaps are 37% and 9 thousand euros, respectively; the 90-10 percentile differences are almost 3 times larger. Based on our estimates, 25% of the firm-year observations should have invested to acquire 6% or more capital, and expand their labor force by 15% or more. On the contrary, another 25% of firms should have sold 1% or more or their assets, and over 10% of observations should have reduced their labor demand by 1% or more. These findings are indicative of suboptimal investment and employment policies, and suggest that output gains might be attainable through a reallocation of resources.

Second, we show that the variation in firm-level MRP-cost gaps is related to the extent of financial frictions and to the degree of labor market rigidities individual firms face. On the capital side, we analyze the impact of asymmetric information in credit markets and the effect of bankruptcy costs, and we study the response of the MRP-cost to idiosyncratic shocks to credit supply. On the labor size, we use MRP-cost gaps of labor to analyze the impact of a labor market regulation that imposes severance payments that vary as a function of firm size.

Economic theory suggests that repeated interactions with financial intermediaries allow firms to overcome possible asymmetric information frictions, and gradually accumulate a capital endowment more consistent with profit maximization ([14]). In line with these theoretical predictions, we find a monotonic negative relation between MRP-cost gaps for capital and the length of the lending relationships of a firm with its current lenders. We estimate that the amount of investment needed to close the gap is worth 25% of the installed capital for firms with newly established lending relationships; this amount reduces to 10% after three years, and to 6% after 10 years of continuous bank-firm interactions. Importantly, the benefits associated with tighter bank-firm relationships are entirely concentrated among those borrowers that operate with an insufficient capital endowment, and they are stronger for highly productive firms. Both findings are consistent with the predictions of economic theory, according to which, ceteris paribus, the shadow cost of capital is higher for more productive capital-constrained firms.

Then we show that the variation in MRP-cost gaps is related to the costs of bankruptcy procedures. To do so, we use cross-province variation in the length of bankruptcy litigations across Italian provinces. We find MRP-cost gaps of observationally similar firms are significantly lower in jurisdictions with shorter bankruptcy litigations. This statistical relationship holds even if we restrict our focus to cross-province variation within the same industry-year-macro region (North-Center-South) into account for other socio-economic differences across geographical regions of Italy ([15]; [16]).

Next, we analyze how the MRP-cost gap of capital responds to changes in the supply of credit. A major challenge in answering this question is to separately identify time-varying credit-supply shocks from simultaneous firm-borrowing demand shocks. To unravel the demand and supply channels, we construct firm-time-specific credit supply shifters. We adopt a shift-share approach that, by leveraging on the granularity of the bank-firm matched records from the Credit Registry, allows us to disentangle nationwide changes in credit supply of individual financial institutions from the idiosyncratic credit demand for their borrowers ([17]; [18]).[3] Consistent with the theoretical prediction that variation in gaps across firms captures heterogeneous shadow costs of capital, we find that, all else being equal, the exposure to a positive supply shock reduces the MRP-cost gaps, whereas a negative credit-supply shock increases them. We find that the response of MRP-cost gaps to credit-supply shocks is substantial for capital-constrained firms, especially the response to positive supply shocks, and that the sensitivity of gaps to credit shocks is particularly strong for more productive firms. On the contrary, the MRP-cost gaps of firms with zero or negative MRP-cost gaps (i.e., those that operate with a capital endowment close to or above target) show a small or no response to credit-supply shocks. That is, by and large, this group of firms respond to an expansion in the credit supply by rolling over their debt, rather than by undertaking new investments, and does not appear to be affected by a credit contractions.

Finally, we analyze the relation between labor gaps and labor market regulations. During our sample period, the provisions of the Italian Workers Statute imposed large severance

3. A contemporaneous work, [19], uses firm-bank matched records from the Italian Credit Registry to construct firm-level credit supply shifters for a subsample of large Italian corporations, to study the impact of credit availability on firm-level productivity.

payments to firms employing more than 15 employees, but significantly smaller payments to firms with 15 or fewer employees ([20]; [21]).[4] Size-dependent firing costs are an adjustment cost that generates variation in marginal revenue products and, if not undone by properly designed wage contracts ([22]), generates misallocation. We find that as the 15-employees threshold is approached, the average gap between the marginal revenue product of labor and wages increases. Higher labor costs also affect firms above this threshold, inducing them to operate with a smaller labor force than the one they might have chosen in the absence of the size-dependent regulation. From a dynamic point of view, we test the local response of firms labor demand to productivity shocks. We estimate that a 1% positive increase in firm-level productivity increases the rate of under-employment by 5 percentage points for firms at the threshold (15 employees), relative to firms immediately below the threshold (14 employees). These results are consistent with the hypothesis that the government-mandated severance payments curb economic growth by discouraging firms from increasing their size despite the growth opportunities that might be available.

Importantly, our research highlights that, for both capital and labor, the dispersion of MRP-cost gaps and the relation between gaps and market frictions is entirely driven by variation in marginal revenue products. Borrowing costs and wages, by contrast, display a limited cross-sectional variation. This finding suggests market prices are not the instruments that allocate resources across credit and labor market participants.

Other phenomena and frictions (i.e., different from credit and labor market frictions) are likely to contribute to the size and dispersion of the gap between inputs' marginal revenue products and user costs, such as economic uncertainty and real adjustment costs ([7]; [23]). Addressing these concerns, we show that the relation between MRP-cost gaps

4. This size-dependent provision of the Italian Worker Statute (Article 18) was reformed in 2012 and finally abolished in 2014.

and credit and labor market frictions is robust to controlling for age, size, credit rating, firm-level productivity and profitability measures, and hold true if we restrict the analysis to within-industry-year-province variation or to within-firm variation. We also evaluate the robustness of our estimates of the marginal revenue products with respect to alternative production function estimations.

The third set of results in this paper cast light on the aggregate implications of resource misallocation in Italy. We use MRP-cost gaps to estimate how idiosyncratic distortions in input policies translate into aggregate output and TFP losses, and to document how gains from reallocation evolved over time and how they differ across sectors and different geographical regions. We calculate that, in any given year, aggregate TFP and output of the Italian corporate sector could be 3%–4% higher following a reallocation of production factors, by taking resources away from firms that over-utilize them, and redistributing these resources to the most productive producers who are lacking them. The majority of allocative inefficiencies take place within narrowly defined industries (roughly two-thirds), and roughly two-thirds of within-industry misallocation takes place within the same geographical regions. Also, we find that gains from reallocation are one-third higher during periods that are characterized by financial instability – the financial crisis (2008-2009) and following the burst of the sovereign debt crisis (2010-2013) – compared to those estimated during the 1997-2004 period. Examining sectoral heterogeneity, we find that the scope of misallocation is more severe outside of manufacturing industries (i.e., services and construction). This finding is important because data constraints has forced most of the existing literature in this topic to focus on manufacturing industries.[5] Our analysis suggests that this might lead researchers to underestimate the extent of resource misallocation. Finally, we examine

5. Relatively few papers have addressed misallocation in the service sector. Those empirical studies that do, also find that the scope of misallocation appears to be larger in services sectors than than in manufacturing ([24]; [25]; [26]).

the spacial variation in misallocation in Italy. Previous research has documented a large disparity in terms of quality of markets and institutions between Italy's Southern regions and the rest of the country ([27]). Accordingly, we document larger output and TFP losses directly imputable to misallocation in the Southern regions when compared to Northern and Central regions of the country.

Our research contributes to a broad scope of literature interested in studying the impact of market frictions and regulations on firms' real activity. The empirical measures produced and analyzed in this paper (MRP-cost gaps) are linked to theory and, because they vary both between- and within-firms, they allow us to shed light on the differential impact of market distortions across heterogeneous types of firms. We see MRP-cost gaps as a particularly appealing empirical tool for researchers seeking to identify firms that are more likely to be financially constrained and for those interested in measuring the real effects of financial frictions, both of which are key topics in corporate finance and applied macroeconomics. In these respects, the value added of our approach is particularly relevant when studying investment policies of privately owned firms. For these firms, traditional measures such as Tobin's Q ([28]; [29]) or indexes of financial constraints ([30]; [31]) are not computable because there no information available on the market value of their assets and liabilities. By contrast, the estimation of MRP-cost gaps requires standard product variables and information on firm-specific user costs, both of which are observable for private firms, and are becoming accessible to researchers as more administrative databases are being disclosed.[6]

6. The ongoing effort of several national data providers to collect information on firm-level borrowing costs (e.g., the AnaCredit project by the ECB, or the CompNet Network) suggests we should expect databases similar to ours to become soon available in other countries. We hope our work can provide guidelines for future research interested in measuring policy distortions combining information on production, financing, and factor prices.

This paper directly speaks to the literature that studies the impact of a suboptimal allocation of resources on aggregate TFP and output ([6]; [5]; [1]; [32]; [33]; [34]).[7] Our contribution is twofold. First, to the best of our knowledge, our paper is the first to try to characterize the distribution of deviations from firms' first-order conditions using detailed micro-data on borrowing costs and wages, thereby showing how these deviations relate to specific frictions and regulations in factor markets, and how to aggregate them to provide macro assessments. Secondly, substantial empirical evidence documents declines in aggregate TFP and output during economic downturns and, in particular, following episodes of financial instability ([36]; [37]). An open question is whether a change in the scope of resource misallocation, on top of (or instead of) technology shocks, contributes to explaining the co-integration of business-cycle fluctuations and aggregate TFP. Our results speak to this question by showing that, indeed, boom and burst cycles in credit markets can affect aggregate TFP due to a deterioration in the efficiency of capital allocation ([38]; [39]; [40]; [41]).[8]

Relatedly, our work also bridges the misallocation literature and the literature that studies the real effects of changes in the supply of credit by financial institutions. Previous works have analyzed the real effects of credit-supply shocks on firms' input accumulation and revenues (e.g., [44]; [45]; [46]; [47]; [48]) and, more recently, their impact on firm-level productivity ([19]; [49]). By combining our measure of policy distortions with quasi-experimental variation individual firms face in the supply of credit, this paper casts light on the distributional effects of changes in financial intermediaries' lending policies, and on their aggregate implications. Our analysis also sheds light on the relative importance

7. See [2], [3], and [35] for a review.

8. Recent papers examine the aggregate costs generated by firm-specific collateral constraints ([42]) and suboptimal capital structure ([43]).

of the price channel versus the quantity channel in the transmission of credit market frictions to the real economy. We document a substantial rigidity of loan prices, and provide evidence that credit limits (i.e., quantity rationing) are the most salient feature of business loan contracts.[9]

Finally, the analysis of the effects of size-dependent labor market regulations connects this paper to a strand of empirical works in labor economics ([21]; [58]; [59]) and applied macroeconomics ([60]; [61]) that evaluates the micro- and macroeconomic impact of labor market regulations on firm policies.[10] Our approach parallels and extends the one in [13]. Given the widespread presence of size-dependent labor market regulations across countries, and the evidence on the comparability of labor demand functions around the world ([64], [65]), lessons about the impact of the Italian employment protection regulation are likely applicable to other countries and to similar types of government interventions in labor markets.

The paper is organized as follows. Section 1.2 describes the data and the institutional features of the Italian credit and labor market that are relevant for our analysis. Section 1.3 presents the theory underpinning the MRP-cost gaps and illustrates their relationship to market frictions. Section 1.4 estimates the gaps and characterizes their empirical distribution. Section 1.5 explores the relationship between MRP-cost gaps and credit and labor market frictions. Section 1.6 presents firm-level counterfactuals useful to quantify the

9. Economic theorists have emphasized that prices in credit markets are not the instrument used to allocate resources ([11,50]). A body of evidence in the consumer lending market has corroborated these predictions ([51]; [52]; [53]; [54]). Yet besides a few noteworthy exceptions, empirical evidence for firms remains scant, mostly due to the lack of longitudinal micro-level data that provide information on the borrowing costs paid by individual on firms ([55]; [56]; [57]).

10. The analysis of the economic effects of firing costs in [62] is one of the earliest studies of misallocation due to regulation. See [63] for a study the aggregate implications of different forms of establishment-level labor adjustment costs.

magnitude of firm-policy distortions. We examine the aggregate implications of resource misallocation in section 1.7. Section 1.8 concludes.

1.2 Data and Institutional Context

We assemble a comprehensive employee-employer-bank matched database that contains micro-level information on firm-specific wages, borrowing costs, balance-sheet data, and bank credit for the lion's share of non-financial incorporated firms that were active, in Italy, between 1997 and 2013. We assemble our data by merging and harmonizing different administrative and proprietary sources.

We collected detailed information on yearly balance sheets, income statements, and registry variables from Cerved Group S.p.A. (Cerved database).[11] We merge the firm-level dataset with the archives of the national Credit Registry (CR) administered by the Bank of Italy, and to matched employer-employee records from the Italian National Social Security Institute (INPS). The CR provides us with information on firms' credit market participation, debt exposure, and corresponding borrowing cost (interest rates) for each bank-firm credit relationship. The Social Security records allow us to observe wages and a detailed snapshot of firms' workforce composition. We complement these data with information on industry-specific price deflators, industry-specific depreciation rates of fixed assets, and socioeconomic indicators measured at the province level, all of which are collected from the publicly available archives of the Italian National Statistical Institute (ISTAT).[12] From

11. Our database includes only incorporated businesses (limited liability companies), but not sole proprietorship and other non-incorporated firms. The unit of observation is a firm-year, no plant-level information is available. Compared to other publicly available datasets (such as Orbis and Amadeus by Bureau van Dijk Electronic Publishing; see [66]), our database has the advantage of having no selection bias, no issues with merging different vintages, and a substantially richer set of balance sheet, income statement, and registry variables.

12. Data available at https://www.istat.it/en/.

the archives of the Italian Ministry of Justice, we collect information on the average length of bankruptcy litigations in court.

Our final dataset includes 3.9 million firm-year observations, 6.5 thousand firms, and 13.3 million credit relationships. It amounts to circa 90% of the value added produced by the corporate sector in the selected industries, and over 70% of the total value added produced by the whole Italian corporate sector.[13] To the best of our knowledge, ours is the first longitudinal dataset that provides information on both production and financing, as well as firm-specific wages and borrowing costs for the large majority of the corporate sector of a country. Table 1.1 reports the summary statistics of the main variables used in our analysis. Appendix A.1 provides a detailed description of each variable and of the steps followed to clean the database. By all means, our sample is composed predominantly of small and medium enterprises, matching the size and industry distribution of Italian firms.[14] Almost all the companies in the Cerved sample are unlisted, making our dataset particularly suited for the purpose of this study, because market failures are expected to have a greater impact on small and young producers ([67]; [56]; [45]).[15]

Credit market relations – Over 80% of the firm-year observations report access to some form of bank credit (BORROWER=1); only 9% of firms never engaged in any type

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13. We drop the following industries: Agriculture, Mining and quarrying, Utilities, Public administration and National defense, Education, Health services, Activities of membership organizations, Activities of households as employers, and Activities of extraterritorial organizations and bodies to avoid dealing with firms with complete or partial government ownership, or heavily subsidized by the government; Financial and insurance activities and Real estate activities because firms operating in these industries are themselves credit providers. See Appendix A.1 for further details.

14. The median firm in our dataset collects 825 thousand euros per year in revenues, has a book value of fixed assets worth 706 thousand euros, and only 6 employees (average number of employees through the year). The macro-industry composition mirrors the one of the Italian economy: 29% of the observations refer to firms operating in manufacturing (23% of the firms); 54% to firms operating in the service sector (61% of the firms); 17% to firms in construction industry (16% of the firms).

15. In our final sample, only 224 firms are publicly listed.

Table 1.1: Summary statistics

This table reports the summary statistics of the main variables used in the paper. A description of the variables is provided in Section 1.2 and Appendix A.1.

	Mean	Std	p10	p25	p50	p75	p90
REVENUES	3598	11230	142	320	825	2314	6661
TOTAL ASSETS	3246	10321	121	269	706	2027	5986
AGE	12	11	2	4	9	18	28
EMPLOYEES	17	39	1	3	6	14	33
ASSETS TURNOVER	1.47	1.42	0.48	0.82	1.25	1.80	2.54
ROA	0.03	0.18	-0.09	0.01	0.04	0.09	0.16
CASH FLOWS / ASSETS	0.04	0.32	-0.04	0.02	0.05	0.10	0.17
BANK LEVERAGE	0.44	0.45	0.00	0.06	0.35	0.65	0.98
LENGTH RELATIONS^{mean}	3.6	2.6	0.9	1.6	3.0	4.9	7.1
LENGTH RELATIONS^{wmean}	3.8	2.8	0.9	1.7	3.0	5.3	7.9
LENGTH RELATIONS^{lead}	4.1	3.6	0.8	1.3	3.0	5.8	9.5
NUMBER RELATIONS	4.1	3.5	1.0	2.0	3.0	5.0	8.0
CREDIT RATING	5.4	5.7	2.0	4.0	5.0	7.0	8.0
LENGTH BANKRUPTCY CASE	8.2	2.0	6.1	6.3	7.9	9.6	10.8
BORROWER	0.80						
MANUFACTURING	0.31						
SERVICES	0.53						
CONSTRUCTION	0.17						
OBSERVATIONS	3933209						
FIRMS	650489						

of credit market transaction at some point between 1997 and 2013. Bank debt is worth on average 43% of firm total assets (54%, if we consider only firms with outstanding debt obligations).

Exploiting the panel dimension of the CR database, we gauge information on the number and length of active credit relationships between firms and individual credit institutions. On average, firms have four active credit relations with financial intermediaries (NUMBER RELATIONS$_{it}$).[16] The variable LENGTH RELATION$_{it}^{wmean} = \sum_{b \in \mathcal{N}_{it}^B} \frac{\text{Credit}_{ibt}}{\text{Credit}_{it}} \cdot$LENGTH RELATION$_{ibt}$ measures the (weighted) average length of active relations, where LENGTH RELATION$_{ibt}$ measures the number of years of continuous relationship between firm i and its lender b, and $\mathcal{N}_{it}^B$ is the set of all its active lenders at time t, and $\frac{\text{Credit}_{ibt}}{\text{Credit}_{it}}$ is the share of total credit provided by each lender. We also construct a second proxy that measures the length

16. Multi-bank relations are a wide-spread phenomenon in business lending, including the United States ([68]).

of the relationship with the most important lender in terms of outstanding credit (LENGTH RELATION$_{it}^{lead}$) and, for completeness, we compute the unweighted average length of relations (LENGTH RELATION$_{it}^{mean}$). The three relationship variables are, by construction, bounded between 0 (no credit relations) and 16 years (the span of our sample). A comparison of the three measures offers important insights into the nature of firm-bank interactions. The data highlight that credit relationships, once established, tend to be quite stable. The average relationship lasts over 5.4 years, about one-third of the span of our sample. Moreover, Table 1.1 shows that LENGTH RELATION$_{it}^{mean}$<LENGTH RELATION$_{it}^{wmean}$<LENGTH RELATION$_{it}^{lead}$. This finding indicates that, while engaging in multiple relations, not all of them are equally important or equally long-lasting. This evidence is in line with the empirical findings reported in [56] for small firms in the United States, and corroborates the theoretical predictions that banks gradually expand their credit supply as they develop a tighter relationship with their borrowers ([14]).

For each firm-year observation, we have information on their CREDIT SCORE measured by Altman Z-score ([69]; [70]). This credit-rating metric is widely used by Italian financial intermediaries in their assessment of firms' creditworthiness (see [71]). It ranges from 1 to 9, with lower numbers (1–4) indicating high solvency and low risk, and higher numbers (7–9) indicating troubled economic conditions and high default risk. Return on Assets (ROA), ASSETS TURNOVER (Revenues/Assets), and CASH FLOWS/ASSETS are measures of profitability, also commonly used in banks' credit assessments.

Finally, we construct an empirical proxy of the deadweight costs incurred in case of bankruptcy. Using data from the Italian Ministry of Justice, we collect information on the average length of bankruptcy trials. For every Italian province, we calculate the average length of cases concluded in years 2005-2007 (LENGTH BANKRUPTCY). The length of the bankruptcy litigations increases the deadweight loss in case of bankruptcy, because the lender is more exposed to borrowers' moral hazard behavior, and the market value of firms' assets typically decays during the period of automatic stay.[17] The data show it takes, on average, almost nine years to resolve a bankruptcy dispute through Italian courts. The standard deviation is two years, with judgments taking "as little as" three years to become final in some provinces, but 13 years in others. We return to sources of variation in this variable in section 1.5.[18]

Labor market relations – Two institutional features of the Italian labor market are important for our paper. The first is the wage-setting mechanism. In Italy, wages are predominantly determined by a two-tier bargaining structure: (1) the first-level bargaining is collective and takes place at the national-sectoral level. It determines the general terms and conditions of employment for different occupations and basic minimum-wage guarantees (*minimi tabellari*); (2) bargaining at the second-level takes place at the regional level or at firm level, and it allows firms and workers to supplement national contracts. Second-level bargaining is optional, and, importantly, it is restricted to upward wage adjustments with respect to the minimum wage guarantees set by the first-level negotiations.[19][20] Several papers have documented that second-level bargaining is rarely used, and only by medium-large firms. For example, [72] finds that less than 20% of firms with more than 20 em-

17. According to the World Bank's "Doing Business" report, Italy ranks 160th out of 185 countries in the enforcing contracts indicator. The poor performance of the Italian legal system largely due to extremely long judicial proceedings. The same report highlights that, in Italy, it takes on average 1,210 days to resolve a commercial dispute through the courts, which is about four times the number of days needed in the United States and three times the number of days needed in the UK and in Germany.

18. See Appendix A.1 for further information about this variable and its geographical variation.

19. The general terms and conditions of employment contracts and minimum-wage guarantees agreed upon in the first-level bargaining are renegotiated, for different occupations, every four and two years, respectively. The amendments to the national contracts renegotiated in the second-level bargaining are valid for four years.

20. Only in well-delimited cases of firm's restructuring or crisis, second-level deals can (temporarily) cut wages below the nationally set sectoral minimum. Still, although legally possible, evidence of firm-level agreement envisaging a decrease in the wage below these minima is scant (see [72]).

ployees use secondary bargaining. This suggests that, although *de jure* wages could adjust upwardly via firm-level bargaining, *de facto* they are anchored to the occupational wage rate periodically set at the national level.

The second institutional feature is the stringent employment protection regulation and its size-dependent nature.[21] Under the Italian employment protection legislation in place during our sample period, individual and collective dismissals of workers with open-end contracts are only allowed on a "just cause" basis. When workers appeal to the court against dismissal, and judges rule the dismissal unfair, firms must provide compensation in the form of severance payments that vary according to firm size. For firms above 15 employees, the firing costs are substantial. Under Art.18 of the Italian Worker's Statute (Law 300/1970), such firms are obliged to reinstate the unfairly dismissed worker, unless the worker opts for a severance payment of at least 15 months of salary. Moreover, employers also have to compensate unfairly laid-off workers for the forgone wages in the time elapsing between the firm's dismissal and the final sentence. This process can take up to five years due to the inefficiency of the Italian legal system. Thus, a firm larger 15 employee faces severe expected firing costs when it attempts to scale down its workforce ([20]; [21]).[22] For firms with 15 or fewer employees, Article 18 does not apply, and their expected firing costs in case of unfair dismissals are substantially lower: they must compensate unfairly dismissed workers with a severance payment that varies between 2.5 and 6 months of salary or, as an alternative to the severance payment, firms can opt for reinstating the worker.

21. According to the OECD index of strictness of employment protection regulation, Italy ranks fifth among the OECD countries. Size-dependent regulations in labor markets are common in both developed and developing countries (see [60]). [73] and [61] analyze the effect of size-dependent regulation in France; [74] in Portugal; [75] in Sri Lanka; [76] in India; in the United States under the US Affordable Care Act, penalties are levied against firms with more than 50 full-time employees that do not offer health care insurance to their employees.

22. Article 18 was substantially reformed in 2012 and finally abolished in 2014.

1.3 A Theory of Gaps

Let us consider a neoclassical environment with homogeneous producers and no risk. When input policies are fully unconstrained, firms accumulate assets and hire labor up to the point where their marginal revenue products are equal to their user costs. In this section, we show this intuition can be generalized to a more realistic framework with heterogeneous producers, where capital structure matters and default risk is endogenous. Appendix A.3 provides a full description of the model.

Economic environment – Consider a firm run to maximize the present discounted value of cash flows to risk-neutral shareholders in an environment where firms are heterogeneous with respect to the realization of firm-specific revenue productivity (ω_{it}, TFPR). Every period, the manager observes the realization of productivity, and then he decides whether (i) to repay its outstanding debt or (ii) default and exit. From a firm' standpoint, a default on bank debt is the optimal decision when the realization of ω is below an endogenously determined threshold level $\bar{\omega}$ ([77]).[23] If the firm is worth more as an ongoing concern, the manager repays its obligations, and he chooses new factor demands (capital K_{it+1}, labor L_{it}, and intermediate inputs M_{it}) and how to finance these purchases (bank debt B_{it+1}, internally generated cash flows, or capital injection from shareholders). In case of default, creditors acquire ownership and control of the firm. They produce during the current period, and liquidate the firm at the end of the period. We assume liquidation is costly, as a fraction $X \geq 0$ of firm assets are lost during the bankruptcy process.

23. Revenue productivity is a combination of technical Hicks neutral productivity and consumer demand ([78]). We assume TFPR evolves stochastically following a first-order Markov process. Because today's investment becomes productive tomorrow ($K_{it+1} = (1-\delta)K_{it} + I_{it}$), uncertainty about the realization of ω_{it+1} generates idiosyncratic investment risk, which makes capital and debt imperfect substitutes in the firms' problem and generates endogenous default risk.

Firm policies and MRP-cost gaps – We heuristically characterize firms' investment policies using the augmented Euler equation of capital and the first-order condition for labor.

We assume new capital injections from shareholders are costly and restrict our attention to cases in which debt is the marginal source of financing for incremental investment.[24] We consider a credit market where lenders offer loan contracts that consist of a single interest rate for each group of observationally similar firms ($r_{it+1} = \bar{r}_{t+1}$), and deal with diversity by rationing those firms within the group that have a loan demand exceeding the loan offer ([11]), which is tied to firms' net worth $B_{it+1} \leq \lambda_{it} K_{it+1}$, $\lambda_{it} \geq 0$ ([81]).[25] A lower λ reflects higher deadweight costs of bankruptcy and/or a higher perception of credit risk by banks. As a result, a firm might prefer to pay a higher interest rate in order to obtain a larger loan, but charging higher interest rates would conflict with the purpose of the bank and its classification scheme. We return to this point below.

In this environment, the investment optimality condition is characterized by the following equation[26]

---

24. This assumption is largely consistent with what we find in our data, in which over 99% of firms are not listed in the stock market, and 80% of the firm-year observations borrow from financial institutions to finance their operations. Of the remaining 20% of the observations, 80% finances capital expenditure with some combination of self-financing and trade credit, and less than 5% uses only capital from shareholders, either in the form of debt from shareholders or in-kind contributions. A large literature addresses the evidence of, reason for, and consequence of the limitation of equity financing (e.g., [79]; [80]; [50]).

25. The interest rate $\bar{r}_{it+1}$ and the tightness of the borrowing constraint λ_{it} are set jointly to maximize bank profits when lending to firms similar to firm i. Pooling observationally similar borrowers, banks set the interest rate based on the expected probability of default for firms similar to firm i, and may cope with risk imposing a borrowing constraint that links credit supply to firms' net worth. For every group of similar borrowers, banks can choose multiple lending contracts, defined by the pair $(\bar{r}, \lambda)$. For example, a competitive lender might follow a two-step optimization process. As a first step, interest rates are chosen to maximize expected profits from borrowers similar to type i. Then λ_{it} is chosen to satisfy the zero profit condition, irrespective of firm-specific productivity, which is unobservable to the bank. A similar two-step optimization can be followed by a monopolistic competitive lender that faces a downward-sloping residual demand for its financial services.

26. [38] derive a similar expression in a model with no default risk.

$$
\begin{aligned}
\rho \int_{\bar{\omega}}^{\infty} \left[MRP^K_{it+1} - (\bar{r}_{t+1} + \delta)\right] d\Phi(\omega_{it+1}|\omega_{it}) = \quad & \psi_2^K(K_{it}, K_{it+1}) + \\
& \rho \int_{\bar{\omega}}^{\infty} \psi_1^K(K_{it+1}, K_{it+2}) d\Phi(\omega_{it+1}|\omega_{it}) + \\
& \chi_{it}(1 - \lambda_{it}) \\
& \equiv \tau^K_{it} .
\end{aligned}
\tag{1.1}
$$

where $\Phi(\omega_{it+1}|\omega_{it})$ denotes the conditional density function of TFPR. The left-hand side represents the difference between the marginal revenue product of capital and the user cost of capital $(r_{it+1} + \delta)$. On the right-hand side, the first and second line denote real adjustment costs of capital ([82]). $\psi^K(K_{it}, K_{it+1})$ is an adjustment cost function of capital, and $\psi_j^K(\cdot)$ the derivative with respect to its jth argument. The existence and impact of these costs on investment policies might be related to firms' lifecycle (e.g., age and size) or product market conditions ([7]). The term in the third line - $\chi_{it}(1 - \lambda_{it})$ - is the *shadow cost of capital* firms face. In the presence of binding credit constraints, the gap between the marginal revenue product and the user cost of capital is an increasing function of the multiplier attached to the borrowing constant ($\chi_{it} \geq 0$) and of the tightness of the constraint $(1 - \lambda)$. We group the terms on the right-hand side and denote them by τ^K_{it}. Abstracting from the impact of adjustment costs, MRP-cost gaps are positive for credit-constrained firms. Their magnitude is proportional to the degree of credit market frictions (e.g., asymmetric information frictions and bankruptcy costs) individual producers face.

Similarly, we express the first-order condition that characterizes optimal employment policies isolating the difference between the Marginal Product of Labor and its user cost (w_{it}) from a residual quantity τ^L_{it}

$$MRP^L_{it} - w_{it} = \quad \psi^L_2(L_{it-1}, L_{it}) + \rho \int_{\bar{\omega}}^{\infty} \psi^L_1(L_{it}, L_{it+1}) d\Phi(\omega_{it+1}|\omega_{it}) \\ \equiv \tau^L_{it}. \tag{1.2}$$

Intuitively, when labor is flexibly hired on the spot market after the realization of productivity, firms choose labor demand equalizing the marginal revenue product of labor to the wage rate. The presence of labor adjustment costs ($\psi^L(L_{it-1}, L_{it})$) invalidates this neoclassical prediction ([63]).[27] For our purposes, the incidence of adjustment costs that vary as a function of firm size is particularly relevant. The following adjustment cost function models the size-dependent provisions of Article 18 of the Italian Worker Statute:

$$\psi^L(L_{it-1}, L_{it}) = \begin{cases} \frac{c^L}{2} \frac{(\Delta L_{it})^2}{L_{it-1}} & if \quad L_{it-1} < \bar{L} \\ \left(\mathbf{1}_{[\Delta L_{it} < 0]} f^L_i\right) \Delta L_{it} + \frac{c^L}{2} \frac{(\Delta L_{it})^2}{L_{it-1}} & \text{otherwise}, \end{cases}$$

where f^L_i is a size-dependent, government-mandated severance payment that firms with a workforce larger than $\bar{L}$ (=15, under Article 18) have to pay to laid-off workers. Because firing costs are only born by companies whose employment is above $\bar{L}$, MRP-cost gaps for labor are expected to display a discontinuous behavior around the threshold.

Discussion – The characterization of firm policies in terms of MRP-cost gaps is convenient. From an empirical point of view, realized MRP-cost gaps are measurable quantities, once estimates of marginal revenue products and information of user costs are available. Thus, they can be used to cast light on the distribution of the unobservable residuals τ^K_{it} and τ^L_{it}, and to test the incidence of specific types of frictions and regulations that affect firm policies. On the capital-side, the gap τ^K_{it} is a particularly valuable empirical tool for investi-

27. [83] and [13] construct similar value of the marginal product minus wage gaps to study the impact of changes in the employment protection regulation in Chile and Spain.

gating the efficiency of investment policies for privately owned firms. For them, traditional measures, such as Tobin's Q or indexes of financial constraints (e.g., [30] or [31]), are not computable because no information is available about the market value of firm's assets and liabilities.[28]

It is important to emphasize that the role plaid by price adjustments, or lack of adjustment thereof, in interpreting the sign and magnitude of MRP-cost gaps. As shown in equations (1.1) and (1.2), when borrowing costs and wages do not vary to accommodate factors demands of heterogeneous producers, MRP-cost gaps capture the pass-through of credit and labor market frictions to firm policies via distorted accumulation of capital and labor. The interpretation of τ^K and τ^L changes when prices are the instruments that allocate resources in capital and labor markets.

In Appendix A.3, we consider a credit contract by which banks do not constraint their credit supply but adjust the interest rate as a function of firm characteristics (bank leverage, capital endowment, productivity) and in response to credit market frictions (bankruptcy costs): $r_{it+1} = r(K_{it+1}, B_{it+1}, \omega_{it}, X)$. Under this credit contract, anything that affects the firm-specific likelihood of default, cost of credit provision, or loss given default affects individual firms' investment decisions and the allocation of credit through an adjustment of the cost of credit. In this case, the term $\chi_{it}(1-\lambda_{it})$ is replaced by the term $\left(\frac{\partial r_{it+1}}{\partial K_{it+1}} + \frac{\partial r_{it+1}}{\partial B_{it+1}}\right)$, and positive gaps would no longer signal constrained access to credit.

Similarly, the characteristics of the wage contract affect the interpretation of the labor gap. Since the seminal work of [22], it is well known that, in the absence of contractual and market frictions, the transfer f_i^L can be neutralized by an appropriately designed wage

28. Unable to observe user costs of capital and/or labor, previous literature has frequently relied on both time-specific effects and firm-specific effects in the empirical specifications to control for the variation in these terms. See [84] or [31]. A noteworthy exception is [85], who proposes an implementation of the q-theory of investment using variation in bond prices.

contract: the firm reduces the entry wage of the worker by an amount equal to the expected present value of the future transfer, so as to leave the expected cumulative wage bill arising from the employment relationship unchanged. On the contrary, when wages are inflexible, firms resort to quantity adjustments that are then reflected in the distribution of τ^L.

The literature suggests several explanations for why the price terms in credit and employment contracts might be rigid. Prominent examples are asymmetric information frictions ([11,12]; [86]), imperfect competition ([87]; [88]), and government interventions that prevent or limit price discrimination, forcing sellers/buyers of credit or labor services to charge/demand the same price in types of transactions that are intrinsically different ([89]; [90]; [46]; [91]). In section 1.5, we document a relative stickiness of interest rates and wages, and provide evidence that is consistent with credit limits and workforce adjustments as the primary margin of adjustment in response to credit and labor market frictions.

Finally, note that besides credit and labor markets frictions, other phenomena contribute to the size and dispersion of realized MRP-cost gaps. Equations (1.1) and (1.2) highlight that economic uncertainty and real adjustment costs naturally drive a wedge between realized marginal revenue products and user costs. Also, market power and imperfect competition, heavy taxation, the bureaucratic costs of doing business, tariffs and subsidies, and frictions in the market of corporate ownership and control also drive a wedge between user costs and marginal revenue products of production factors (see the review in [2]). We design empirical tests that allow us to disentangle the effect of these alternative phenomena from the extent of credit and labor market frictions that individual firms face. For credit market frictions, we focus on the relevance of asymmetric information, bankruptcy costs, and idiosyncratic shocks to credit supply. For labor market frictions, we study the static and dynamic effects of the provisions of Article 18 of the Italian Workers' Statute.

1.4 The Distribution of MRP-cost gaps in the Micro Data

In this Section, we describe the empirical procedure that allows us to produce measurable counterparts of the MRP-cost gaps in equations (1.1) and (1.2). A unique feature of our database is the availability of information on *both* firm-specific wages and interest rates, collected from highly reliable administrative sources, for the lion-share of the corporate sector of a country. This feature gives us a significant edge in obtaining measurable proxies of the distribution of firms' user costs of capital and labor. We estimate realized marginal revenue products of capital and labor following the literature on production function and markup estimation ([9]; [10]). Thus, the empirical counterparts of MRP-cost gaps are

$$\hat{\tau}_{it}^{K} \equiv \rho(1-\hat{P}\{Exit_{it+1}|X_{it}\}) \cdot \left[\widehat{MRP}_{it+1}^{K} - (r_{it+1}+\delta_s)\right] \tag{1.3a}$$

$$\hat{\tau}_{it}^{L} \equiv \widehat{MRP}_{it}^{L} - w_{it}\,. \tag{1.3b}$$

The discount factor is set to $\rho = 0.95$, a standard assumption in the literature ([38]). In order to approximate the conditional expectation in Equation (1.1), we evaluate the expectation of the marginal revenue product minus user costs gap at their realizations, adjusting the latter by multiplying them by the expected probability of exit ($P\{Exit_{it+1}\}$). This procedure naturally introduces an expectational error that is going to generate variation in the estimated MRP-cost gaps ([7]). The probability adjustment accounts for the fact that, because today's investments become productive with a lag, expected returns are lower for firms with higher exit probability.

We estimate expected probabilities of exit via a probit model. The left-hand side variable is an indicator function equal one when we observe the firm exiting in year $t+1$.[29]

29. The dummy variable $\text{E}{\small\text{XIT}}_{it+1}$ takes value one in year t when a firm does report any balance sheet and income statements from year $t+1$ onward. It also takes value equal one for firms that report in $t+1$ zero

The explanatory variables include the set of state variables of the firm problem as well as a set of firm-specific and macro-financial variables that allow us to better capture firms' expectations (see Appendix A.8 for details). Our estimates of the unconditional probability of exit is 7.3% on average, matching the unconditional exit rate in our sample. In line with the guidelines of economic theory, the estimated exit probability is decreasing in firm's size, age, productivity, and credit rating. It is higher for more leveraged firms and for those producers that defaulted on their debt obligations.

In the remaining of this Section, we describe our proxies of the user costs of capital and labor, illustrate the estimation procedure of marginal revenue products, and finally present the estimates of the MRP-cost gaps.

1.4.1 User costs of Capital and Labor

1.4.1.1 The User Cost of Capital

We construct firm-time varying user costs of capital as the sum of borrowing costs and depreciation rates of fixed assets ($r_{it+1} + \delta$). Industry-specific depreciation rates (δ) are collected from the Italian Statistical Agency (National Accounting Tables). To measure the borrowing rate r_{it+1}, we use the Average Percentage Rates (APR) on firm-bank matched loans from the Credit Registry (Taxia database).[30] While alternative credit products are

amounts of two of the three production inputs: capital stock, wage bill expenses, or purchases of intermediate inputs.

30. The Taxia database covers the large majority of the financial intermediaries operating under the supervision of the Bank of Italy. Until 2003, the subgroup of banks in Taxia was composed by around 90 banks, accounting for more than 80% of total bank lending. Starting from 2004, the pool of banks in Taxia sample has been expanded to 103 national banks and 10 branches and subsidiaries of foreign banks. Banks in the Taxia sample must report information on the APR charged to every borrower if the total amount of credit granted plus guarantees provided by the borrower exceeds 75,000 euro. Taxia allows us to distinguish between two types of loans: term loans and loans backed by account receivables. We use the APR on term loans as a baseline rate, and the APR on credit backed by receivables when the interest rate is not available (25% of the cases). 73% of firms with an outstanding balance of term loans also have outstanding credit backed

available to firms, bank loans represent around 3/4 of total bank debt and they are the typical credit product used to finance expenditures in fixed assets.[31] We calculate the firm-year-level APR as follows. When multiple banks are lending to the firm, we compute the weighted average APR with weights equal to the fraction of total loans granted by each institution. When a firm has only one outstanding loan from a single bank, no aggregation is needed.[32]

Firms that do not actively engage in credit market transactions (20% of our sample) pose an empirical challenge because we have no information on borrowing rates for them. These observations are of interest since they allow us to investigate the relationship between credit market participation and firm policies. Thus, we would like to construct a plausible estimate of their user cost. There is ample empirical evidence, corroborated by the analysis of Section 1.5, that banks set their rates based on a limited number of observable characteristics ([92]; [57]). Moreover, it is well established that financing of small and medium firms - the lion share in our data - is tied to their local credit markets as proximity between borrowers and lenders facilitates information acquisition ([93]; [94]). We use firm characteristics and geographical location to infer the interest rate that non-borrowers could have been charged had they engaged in credit market transactions. Within each year and local credit market - defined by the perimeter of Italian provinces -, we estimate loan

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by receivables. In terms of observable characteristics, firms that use only one or the other credit product are similar. Two APR are similar in level (on average: 5.6% term loans, 6.2% credit BAR), highly correlated with each other (raw correlation 39%), and they correlate in the same way with firm characteristics.

31. Appendix A.2.1 shows that changes in bank loans can explain a larger share of the variation in investment rates and that the elasticity of investment with respect to changes in loans is three times as large as the elasticity with respect to changes in credit line draws.

32. That is, we calculate the value-weighted average APR for each firm-year as $r_{it+1} = \sum_b w_{bit} r_{ibt+1}$, where $w_{ibt} = {}^{Loans_{ibt}}/_{\sum_b Loans_{ibt}}$. When we observe multiple APRs for the same firm-bank pair, we calculate the weighted average using as weights the share of interest expense imputable to each loan. See Appendix A.1 for details.

pricing regressions in the relationship level database. The set of predictors includes industry, age, assets, credit score, assets turnover, ROA, and whether the firm has any credit in default during that year of the previous ones.[33] These variables are selected to meet two criteria. On the one end, they represent a parsimonious choice that ensures the existence of a common support between the group of borrowers and non-borrowers for every year-market combination. On the other hand, they are observable indicators commonly used by banks to assess firms' riskiness and creditworthiness. The Altman Z-score is a widely used metric used by Italian banks to assess firms credit risk ([71]) and the Cerved database is the source of firms' balance sheet information used by banks to collect balance sheet data on current and perspective borrowers. Moreover, our data on firms total debt exposure is the same information that banks can obtain when they send a query to the CR.[34] The pricing regression is estimated on the subsample of newly established relations (LENGTH RELATION$_{it} \leq$ 1 year).[35] Appendix A.2.2 provides a detailed description of this procedure and provides a number of robustness tests of our estimates.[36]

33. Italian provinces are the natural candidates for the definition of local credit markets for small business lending (see [95]). They constitute administrative units comparable to US counties. The the Bank of Italy uses the administrative boundaries of provinces as a proxy of local credit markets for regulatory and supervisory purposes.

34. Through the Central Credit Registry financial companies supervised by the Bank of Italy exchange information about the global risk position (total outstanding banks credit and total credits in default) of their customers and of those of other institutions. After it receives information on the loans granted by the participating intermediaries to individual customers, the Bank of Italy aggregates the data for each borrower and calculates their total debt exposure vis-a-vis the financial system, and possible amounts past due or in default.

35. The focus on new relationships is important because non-borrowers would be new customers for the bank in case they approach them. Moreover, for new relationships, we do not have to account for the dynamics of firm-bank relationships, and the acquisition of soft information and lower monitoring costs that repeated interactions bring about.

36. Matching-on-observables raises concerns related to unobserved heterogeneity - as soft information might be available to the bank but not to the econometrician -, and to possible selection issues, since only transactions for which borrowing/lending is economical for both firms and banks are observed. We discuss these issues in Appendix A.2.2.

Firms that engage in credit market transactions, but for which we are unable to observe the interest rate, represent a second empirical challenge for the construction of the user cost of capital. These observations refer to firms that only use credit lines; to those firms borrowing from lenders are not part of the group of banks in the Taxia database; or to firms that borrow small amounts that are not reported in the CR.[37] For these observations, the missing price problem is less severe because, beside firm-specific characteristics and geographical location, we can augment the pricing regressions with information about total bank leverage, the length of each individual credit relation, the total number of lending relations, and dummies that identify lenders (see Appendix A.2.2).

Table 1.2 (panel a) presents summary statistics describing the distribution of user costs of capital and its components. We present them for the whole sample, and splitting observations into borrowers with outstanding loans (BORROWERS-LOANS), borrowers with no loans (BORROWERS-NOLOANS, i.e. firms with no outstanding loans but positive draws from credit lines), and non-borrowers (NON-BORROWERS). For observations belonging to the first subsample, the interest rate is observed; for the last two groups, we report the estimated interest rate. Consider first the subsample of borrowers with loans. Over our sample period, their user cost of capital was on average 16.4%. One-third of it is imputable to the borrowing cost (5.5%), and two thirds to depreciation rates (10.8%). On average, the borrowing costs inferred for credit lines-only borrowers and for non-borrowers are respectively 40 and 130 basis points higher than the ones observed for borrowers, reflecting the compositional differences among the observations that form the three sub-samples. In Appendix A.1 we show that, compared to firms with outstanding bank loans, producers

37. The debt amounts from the Credit Registry are recorded at a monthly frequency. To harmonize them with firms' annual balance sheets, we calculate the average credit exposure of a firm across all lenders in each fiscal year. Intermediaries report to the Credit Registry any relationship with a client whose total amount of credit granted plus guarantees provided by the borrower exceeds 30,000 euro (75,000 euros before 2008). See Appendix A.1 for details.

Table 1.2: Marginal revenue products, user costs, MRP-cost gaps, and percentage deviations

Panel a reports summary statistics describing the distribution of the marginal revenue product of capital (MRP_{it}^{K}) and labor (MRP_{it}^{L}). MRP_{it}^{K} is expressed in percent; MRP_{it}^{L} is expressed in thousands of Euros. Panel b reports summary statistics describing the distribution of the annual percentage rate (APR) on bank loans (r_{it+1}), depreciation rate on capital (δ_s), the sum of the two (user cost of capital, $r_{it+1}+\delta_s$), and wage (user cost of labor, w_{it}). Interest rates, depreciation rates and user costs of capital are expressed in percentages; wages are expressed in thousands of Euros. Panel c presents the descriptive statistics of the distribution of MRP-cost gaps τ_{it}^{K} and τ_{it}^{L} . Capital gaps are expressed in percentages; labor gaps are expressed in thousands of Euros. Panel d reports summary statistics of the distribution of percentage deviations from target input demands ($\frac{L_{it}^{*}-L_{it}}{L_{it}}$, $\frac{K_{it}^{*}-K_{it}}{K_{it}}$) and implied deviation from target output $\frac{Y_{it}^{*}-Y_{it}}{Y_{it}}$, which are expressed in percentages. Summary statistics are reported for the full sample and, for capital-related variables, also splitting the sample into borrowers with active loans (BORROWER-LOANS = 1) , borrowers with credit lines only (BORROWER-NOLOANS = 1), and non-borrowers (BORROWER = 0). Block-bootstrapped standard errors are in parenthesis.

	Whole Sample				*Borrowers-Loans*				*Borrowers-NoLoans*				*Non-Borrowers*			
	MEAN	MEDIAN	10^{th}	90^{th}	MEAN	MEDIAN	10^{th}	90^{th}	MEAN	MEDIAN	10^{th}	90^{th}	MEAN	MEDIAN	10^{th}	90^{th}
Panel a: User Costs																
$r+\delta$	16.4	16.7	12.1	19.9	16.4	16.4	12.6	20.0	15.9	16.3	11.1	19.3	16.8	17.3	12.0	19.3
r	5.9	5.8	3.5	8.4	5.5	5.3	3.0	8.3	5.9	5.8	4.1	8.0	6.8	6.6	4.8	8.7
δ	10.5	11.4	5.6	12.5	10.8	11.4	7.5	12.5	10.0	10.1	5.5	11.9	10.1	10.3	5.6	11.9
w	18.8	17.8	10.7	27.7												
Panel b: Marginal Revenue Products																
MRP^{K}	54.6	19.6	2.8	113.4	44.6	17.7	2.7	180.1	62.0	19.7	2.6	131.4	80.0	27.0	3.4	180.1
	(0.11)	(0.04)	(0.01)	(0.28)												
MRP^{L}	28.0	24.6	9.8	49.1												
	(0.02)	(0.02)	(0.01)	(0.05)												
Panel c: MRP-Cost Gaps																
τ^{K}	36.4	3.2	-12.4	91.6	26.9	1.4	-12.5	71.1	43.8	4.0	-12.4	109.0	60.1	9.8	-12.0	154.4
	(0.10)	(0.03)	(0.01)	(0.26)												
τ^{L}	9.3	6.1	-6.4	28.3												
	(0.02)	(0.01)	(0.01)	(0.04)												
Panel d: Percentage Deviations																
$(K^{*}-K)/K$	15.5	0.4	-1.9	16.6	9.2	0.2	-1.9	12.0	17.3	0.5	-1.8	19.5	32.4	1.2	-1.7	42.1
	(0.04)	(0.00)	(0.00)	(0.08)												
$(L^{*}-L)/L$	10.7	3.0	-7.2	35.4												
	(0.06)	(0.01)	(0.01)	(0.11)												
$(Y^{*}-Y)/Y$	12.0	4.3	-4.0	35.6	9.4	4.0	-3.6	26.1	12.1	4.5	-5.4	37.7	17.8	5.1	-4.6	59.5
	(0.00)	(0.00)	(0.00)	(0.00)												

that do not engage in credit market transactions and those who only used credit lines are younger and smaller; over-represented in Southern regions of Italy, and in industries with lower tangible to intangible assets ratio (such as services).[38] Credit lines-only firms also tend to have shorter lending relationships with their lenders when compared to companies that utilize bank loans. Not by chance, all these variables are commonly regarded as proxies of credit constraints.[39] Consistent with this, the empirical analysis of Section 1.5.1 finds that firms that do not engage in credit market transactions and credit lines-only borrowers tend to have a higher marginal revenue product of capital than borrowers with outstanding term loans.

1.4.1.2 The User Cost of Labor

Employer-employee records from the Italian National Security Institute provide us with detailed information on workforce compensation. We use the average annual wage as a proxy for the user cost of labor w_{it}. We calculate it considering the annualized compensations of all fixed-term contract workers (white collars, blue collars, middle managers, and full-time interns) hired by the firm throughout the year.[40] Table 1.2, panel a shows that the average nominal wage is about 19 thousand euros per year, the median is one thousand euros lower.

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38. See Appendix A.1 for a comparison of borrowers and non-borrowers based on observable characteristics.

39. Because credit lines are a more expensive type of credit and they can be revoked at lenders' discretion, firms should rarely turn to credit lines to finance capital expenditures in fixed assets, unless bank loans are constrained or denied by credit institutions.

40. The firm-level records are aggregated by the Italian National Security Institute and provided to us at a monthly frequency. For each firm-year observation, we first calculate the average monthly wage (simple average) and then we annualize it. While not perfect, this procedure is better than using the annualized end-of-year wage (month of December) because end-of-year compensations are more likely to be susceptive to *una tantum* adjustments.

One may worry that the average wage may differ significantly from the wage paid to hire an extra worker. To address this, we construct an alternative proxy of the user cost of labor using individual workers' wage records from the matched employer-employee panel database. In particular, we calculate the average annualized wage paid by firms to *newly hired* workers in each industry-province-year triplet.[41] The advantage of this measure is that it can be thought of as the cost that a firm would incur when hiring an additional worker in the same industry and labor market. The drawback of this measure is that, by averaging across companies, it washes away any firm-level link between wages and the marginal product of labor. We find that the average wage paid to new workers exceeds the average wages by approximately four thousand euros (18% of the average wage). As we discuss below, our main empirical findings are ultimately unaffected by using this alternative proxy of user costs of labor.

1.4.2 *Identification and Estimation of Marginal Revenue Products*

Without loss of generality, we can decompose the marginal revenue product of an input $X = \{K, L, M\}$ into the Value of the Marginal Product (VMP_{it}^X) and the inverse-markup (μ_{it}^{-1})

$$MRP_{it}^X \equiv \frac{\partial\left(P_{it}(Q_{it})Q_{it}\right)}{\partial X_{it}} = \underbrace{P_{it}\frac{\partial Q_{it}}{\partial X_{it}}}_{VMP_{it}^X}\underbrace{\left(1+\frac{Q_{it}}{P_{it}}\frac{\partial P_{it}}{\partial Q_{it}}\right)}_{\mu_{it}^{-1}} = \theta_{it}^X \frac{PQ_{it}}{X_{it}}\frac{1}{\mu_{it}}. \tag{1.4}$$

41. The employer-employee matched database follows the employment history of a random sample of 20% of every cohort of workers. In our dataset, the subsample of firm-year observations that (i) hires new workers and (ii) for which we have information on at least one wage rate of the newly hired workers from the employer-employee database is 48%.

The last equation decomposes the physical Marginal Product Value into output elasticity (θ^X) and average product ($\frac{PQ_{it}}{X_{it}}$) using the definition of output elasticity. We estimate marginal revenue products taking Equation (1.4) to the data.

We measure average products of capital (PQ_{it}/K_{it}) and labor (PQ_{it}/L_{it}) directly in the data. PQ_{it} is total sales. The ideal empirical measures of capital (K_{it}) and labor (L_{it}) shall capture the flow of services provided by these inputs. Toward this end, we re-construct the sequence of capital from investments in fixed assets (both tangibles and intangibles) following the Perpetual Inventory Method ([96]) and measure labor services in units of effective labor (annual wage bill over average annual wage). The Perpetual Inventory Method provides us with a better proxy of capital services than the book value of physical assets.[42] With respect to other measures - such as the number of workers -, by measuring labor services in effective labor unites we can better accounts for differences in the quality of firms' workforce ([97]).[43]

Output elasticities – We estimate output elasticities via production function estimation. Consider the following log-production function

$$q_{it} = \omega_{it} + \varepsilon_{it} + f(k_{it}, l_{it}, m_{it}, \gamma)$$

where γ is a vector of structural parameters to be estimated. ω_{it} is firm-level productivity, observed by the firm at the moment of its production decisions, and ε_{it} is a production shock taking place after input decisions have been made.

42. See Appendix A.1.6 for details on the construction of the capital sequence using the Perpetual Inventory Method (PIM).

43. Using total wage bill as a measure of labor inputs delivers estimates very similar to the ones obtained using effective labor. Results are available upon request.

We specify a Translog functional form for production technologies f. For the purpose of approximating the full distribution of marginal revenue products, the flexibility of Translog represents a significant advantage over more standard (but less flexible) functional forms such as Cobb-Douglas or CES. Translog does not impose any restriction on the elasticity of substitution of different inputs. Moreover, it allows us to recover a distributions of firm-time specific elasticities that are a function of industry-specific structural parameters γs and of the input-mix utilized by each firm: $\theta_{it}^X = \theta^X(k_{it}, l_{it}, m_{it}; \gamma)$ $X = \{K, L, M\}$.[44]

We estimate production function parameters γ following the structural approach proposed in [9].[45] This approach identifies the parameters of the production function addressing the simultaneity bias that derives from the correlation between input choices and unobserved (to the econometrician) productivity ([98]), and it solves the non-identification problem that affects the estimates of output elasticity with respect to flexible inputs.[46]

The production function estimation is performed separately for every four-digits industry (NACE, rev.2 industry classification system). This allows the structural technology parameters γs to vary by narrowly defined industries (467 in total) that encompass both the manufacturing and non-manufacturing sectors of the economy. We use deflated revenues in place of physical output, and deflate capital and intermediate inputs (measured as total expenditures in raw materials, services, and energy consumption) by the corresponding

44. Consider the following log-version of production functions: $q_{it} = f(k_{it}, l_{it}, m_{it}; \gamma) + \omega_{it} + \varepsilon_{it}$. Under Translog, the expression for output elasticities of any input $X = \{K, L, M\}$ is $\theta_{it}^X = \gamma_X + 2\gamma_{XX} x_{it} + \sum_{x' \neq x} \gamma_{xx'} x'_{it}$. See Appendix A.4 for details.

45. We provide the details of the estimation routine in Appendix A.4 and refer to [9] for a more detailed exposition and its underlying assumptions. We thank the authors of [9] for sharing their code, and to David Rives for his practical advice.

46. [9] shows that the standard proxy-variable approach applied to gross output production functions does not identify the elasticities of flexible inputs, unless the production function takes specific functional forms (e.g. the Leontief case discussed in [99]) or external sources of variation in firms' demand for flexible inputs (e.g. [100]).

industry-year price deflators.[47] Finally, we need to take a stand on the vector of instruments that identify θ^K and θ^L in the estimation routine. We assume capital is quasi-fixed and predetermined.[48] Thus, in principle, k_{it} does not require an instrument. Nevertheless, we use (lagged) firm-specific borrowing costs to construct an additional moment condition that strengthens the identification of the elasticity θ^K, which typically suffers from attenuation bias due to the difficulty to measurement capital services ([101]).[49] Given the institutional features of the Italian labor market, we consider labor a flexible input (chose in period t after observing ω_{it}) but dynamic (subject to adjustment costs). Thus, we rely on l_{it-1} as an instrument for l_{it} and address the endogeneity problem due to correlation with unobserved productivity.

Once estimates of the structural parameters γ are available, we infer the realization of firm-level revenue productivity (TFPR, [78]) as

$$(\omega_{it} + \varepsilon_{it}) = q_{it} - f(k_{it}, l_{it}, m_{it}; \gamma),$$

where lower case letters denote the log of variables. With a slight abuse of notation, we denote $(\omega_{it} + \varepsilon_{it})$ with ω_{it}.

Markups – To estimate markups we follow the production side approach pioneered by the seminal work of [102] and recently revisited by [10]. The identification rests on the theoretical intuition that, conditional on the state variables of the problem, the first-order

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47. While unsatisfactory, this is the predominant approach in the Industrial Organization literature since most of the available firm- and plant-level database, including ours, do not separately report prices and physical quantities of inputs (with the exception or labor, in our case) and/or output. We use industry-specific investment deflators for capital, and industry-specific value added deflators for intermediate inputs. These data are freely available on the website of the Italian National Statistical Agency (http://dati.istat.it/?lang=en).

48. This is a standard assumption, consistent with the capital accumulation equation: $K_{it} = I_{it-1} + (1 - \delta)K_{it-1}$.

49. See Appendix Appendix A.4 for more details, and [100] for a discussion of how information factor prices can be used to identify production functions.

conditions of the cost minimization problem for inputs that are flexible and static provides an expression relating revenue cost shares and output elasticities to markups:

$$\hat{\mu}_{it} = \hat{\theta}_{it}^{M} \left(\frac{\frac{P_{it}Q_{it}}{exp(\hat{\varepsilon}_{it})}}{P_{it}^{M}M_{it}} \right),$$

where $P_{it}Q_{it}/P_{it}^{M}M_{it}$ is the inverse of the expenditure share on intermediate inputs in revenues (directly observed in the data) and $\hat{\theta}_{it}^{M}$ is the output elasticity with respect to intermediate inputs (obtained via production function estimation). We follow [10] and correct expenditures shares using the residuals of a regression of a polynomial function of deflated inputs on deflated revenues. This adjustment helps to net out variation in output not correlated with changes in input utilization (such as the one due to demand, inputs prices, or productivity).[50] The flexibility of the Translog functional form adopted in the production function estimation also helps to addressing this issue.

Table 1.3 displays our estimates of elasticities, returns to scale, markups, and productivity. Block-bootstrapped standard errors are reported in parenthesis ([104]). The deflated revenues of the average firm responds by 4%, 29% and 67% to a one-percent increase in capital, labor and intermediate inputs, respectively, which implies average local returns to scale close to unity. These parameters are precisely estimated and in line with the ones found in the literature.[51] Importantly, our estimates highlight substantial heterogeneity in the parameters characterizing production technologies, both within and across industries.[52] The interquartile rage spans between 57% and 79% for intermediate inputs, and 2%–6%

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50. See Appendix A.6 for more details and [103] for a discussion and application of this methodology.

51. See for example [105], [106], [13], and [9] for estimates referring to manufacturing industries.

52. Appendix A.4 provides a graphical comparison of output elasticities across firms of different age and size. We find a significant decline of θ^{K} with firm size and age, while θ^{L} increases as firms grow older but decrease with firm size.

Table 1.3: Revenue elasticities, returns to scale, markups, and elasticities

This table displays the estimates of firm-level production function parameters, returns to scale, markups, and revenue productivity. We report average, interquartile range, and block-bootstrapped standard errors of the mean (in parenthesis). The first block reports the statistics across all firm-years. The second and third block split the sample into manufacturing and non-manufacturing firms, respectively. In each block, the first four rows of table show the estimates of output elasticities with respect to capital (θ_{it}^{K}), labor (θ_{it}^{L}), intermediate inputs (θ_{it}^{M}). The fourth row reports the estimated returns to scale ($RS_{it} = \sum_X \theta_{it}^{x}$, $X = \{K, L, M\}$). The fifth and sixth rows report the summary statistics of the estimated markups (μ_{it}) and revenue productivity (TFPR, ω_{it}), respectively.

	All Industries		Manufacturing		Non Manufacturing	
	Mean	75-25	Mean	75-25	Mean	75-25
θ^K	0.04	0.04	0.05	0.04	0.04	0.04
	($0.6{\cdot}10^{-4}$)		($0.6{\cdot}10^{-4}$)		($0.6{\cdot}10^{-4}$)	
θ^L	0.29	0.21	0.30	0.16	0.29	0.23
	($2.2{\cdot}10^{-4}$)		($2.2{\cdot}10^{-4}$)		($2.2{\cdot}10^{-4}$)	
θ^M	0.67	0.22	0.67	0.16	0.68	0.24
	($1.9{\cdot}10^{-4}$)		($1.9{\cdot}10^{-4}$)		($1.9{\cdot}10^{-4}$)	
RS	1.01	0.05	1.02	0.05	1.01	0.06
	($2.2{\cdot}10^{-4}$)		($2.2{\cdot}10^{-4}$)		($2.2{\cdot}10^{-4}$)	
μ	1.02	0.16	1.01	0.15	1.02	0.16
	($0.6{\cdot}10^{-4}$)		($0.6{\cdot}10^{-4}$)		($0.6{\cdot}10^{-4}$)	
ω	2.52	0.71	2.64	0.36	2.46	0.90
	($14.5{\cdot}10^{-4}$)		($14.5{\cdot}10^{-4}$)		($14.5{\cdot}10^{-4}$)	

and 18%–38% for capital and labor, respectively. In term of markups, our estimates suggest that, on average, firms price 2% above their marginal cost of production. The right skewness of the distribution drives the dispersion of markups. Firms located at the 75th and 90th percentile of the distribution price 5% and 15% above marginal cost, respectively.

In the Appendix of the paper, we present a number of sanity and robustness checks on our estimates. Appendix A.4 shows that the estimates output elasticities are consistent with the ones obtained using a cost-share approach ([107]). We also discuss the robustness of our estimates with respect to alternative functional forms of production technologies and estimation routines. In Appendix A.6 we conduct a series of robustness checks of our estimates of markups. We find a strong positive correlation between markups and firm's profitability (either EBITDA over total assets or ROA), and with product market concentration measured by the Herfindahl concentration index. Our estimates of firm-level markups also display a strong and positive correlation with productivity (in both levels and changes), which is an empirical relationship documented by previous literature (see [10]).

Marginal revenue products – Combining average products, output elasticities, and markups, we construct estimates of realized marginal revenue products of K and L (Equation 1.4). Table 1.2 (panel b) reports descriptive statistics of their distribution. Over the 1997-2013 period, the median firm in our dataset has a marginal product of capital of 21%, while that of labor is slightly lower than 25 thousand euros.[53] We point out that the estimated marginal revenue product of capital is 1.5 times higher for non-borrowers and 0.5 times higher for those borrowers that access only to credit lines, which suggests that constrained access to credit markets might prevent some firms from harvesting profitable investment opportunities. We will return to the distinction between the three groups of firms in Section 1.5.

Finally, two remarks are in order. First, we treated deflated sales as a measure of physical quantity when estimating output elasticities. Therefore our estimates are potentially subject to the omitted price variable bias discussed in [108], and our estimates of productivity are a proxy for revenue productivity (TFPR). Not controlling for firm-specific output prices would be particularly problematic if estimating physical productivity (TFPQ) was the ultimate goal of this paper ([78]). It is less of a concern for our analysis because TFPR is the relevant productivity measure to test the theory underlying the MRP-cost gaps (see Section 1.3).[54] Second, we must also recognize that our data does not allow to distinguish between single and multi-product firms. If firms operate across multiple industries or produce differentiated goods, our estimates might be biased because the estimation rou-

53. In Appendix A.7, we also investigate the sources of dispersion of *MRP*s. Two findings are worth mentioning. First, marginal revenue products are more dispersed outside manufacturing. Second, the bulk of the dispersion in *MRP*s is found within industries rather than between industries. The within-industry dispersion exceeds the between industry dispersion by a factor of two for MRP^K and a factor of 1.4 for MRP^L.

54. It must be kept in mind, however, that the inability to control for heterogeneous prices may also generate a downward bias in the estimates of output elasticities ([105]) and, thus, of our estimates of marginal revenue products.

tine implicitly assumes a single production function and a single consumer's demand curve faced by each firm (see [109] and [105]). We cannot identify which companies operate across industries because our data reports only the primary industry code of each observation. However, because large firms are more likely to expand their activity across industries, the small size of the producers in our data suggests that multi-product firms are unlikely to be the majority of our sample.

1.4.3 The Variability of User Costs and Marginal Returns, and the Empirical Distribution of MRP-cost Gaps

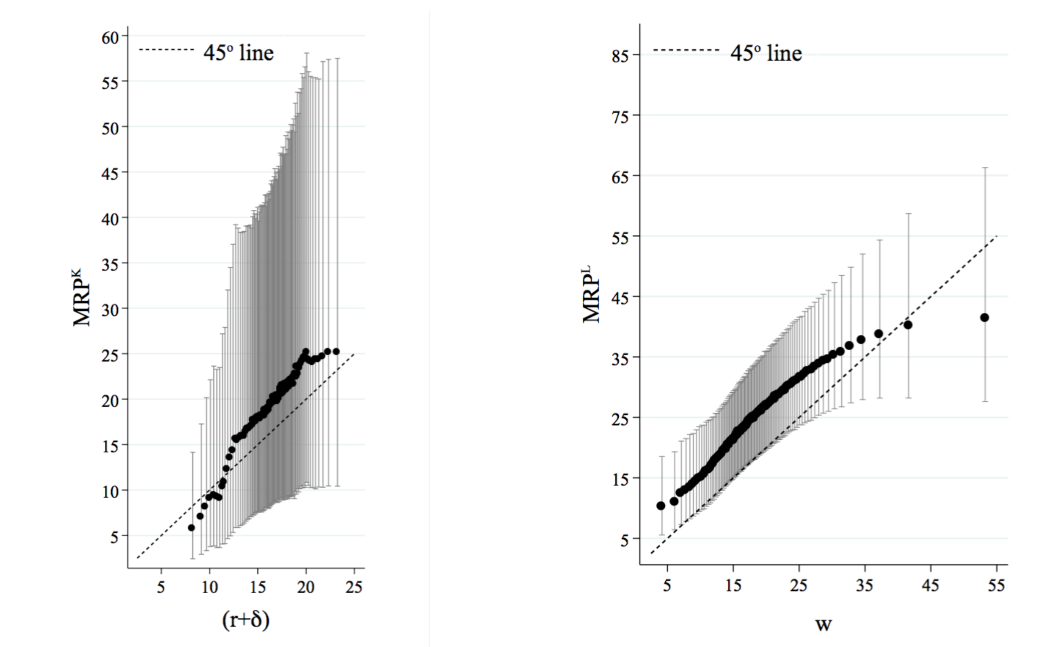
Dispersion in MRP and User Costs – Before presenting the empirical distribution of the MRP-cost gaps, it is instructive to analyze the joint distribution of user costs and marginal revenue products of capital and labor. In Figure 1.1, we parse the data according to the percentile of the distribution of user costs of capital (panel a) and labor (panel b).

Figure 1.1. Joint distribution and dispersion of MRP and user costs

This figure investigates the joint distribution of marginal revenue products and User Costs, and their dispersion. We parse the data according to the percentile of the distribution of user costs of capital (panel a) and labor (panel b). The x-axis reports the median value of the user cost and the y-axis reports the median value and interquartile range of the MRP for the group of observations belonging to the same percentile of the distribution of user costs.

Panel a: Capital

Panel b: Labor



For each percentile, the x-axis reports the median value of the user cost. The y-axis reports the median value and interquartile range of the MRP for the group of firm-year observations belonging to each percentile of the distributions of user costs. Two observations are in order.

First, the central percentiles of the distribution of *MRP*s map onto the corresponding moments of the distributions of the user costs. The correlation between the median (mean) value of MRP and the median (mean) value of user costs within each percentile of the distribution of user cost is 98% (95%) percent for capital and 98% (96%) for labor, with p-values lower than 1%.[55] This finding suggests that user costs are an economically meaningful

55. The correlation between marginal revenue products and user costs is economically and statistically significant also at the firm-level (6% capital and 37% for labor, p-values lower than 1%).

benchmark for the realized marginal revenue products of capital and labor of individual producers, as profit maximization predicts.

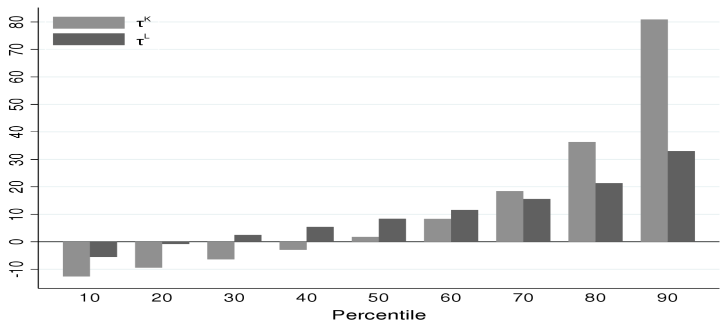
Secondly, the large dispersion of marginal revenue products is in stark contrast with the fairly symmetric and compact distribution of user costs. This is particularly evident in the case of capital. For example, the variation in realized MRP^K within each percentile of the distribution of the $r+\delta$ is greater than the unconditional variation of $r+\delta$. A similar observation applies to the dispersion in MRP^L and wages.

Distribution of MRP-cost Gaps – We combine the estimate of MRP and the observed user costs, to produce empirical counterparts of MRP-cost gaps (Equations (1.3a) and (1.3b). To limit the impact of outliers, we winterize the 2.5 tails of the distribution of τ_{it}^K and τ_{it}^L. Table 1.2, panel c reports summary statistics of our estimates. Figure 1.2 displays their full distribution.

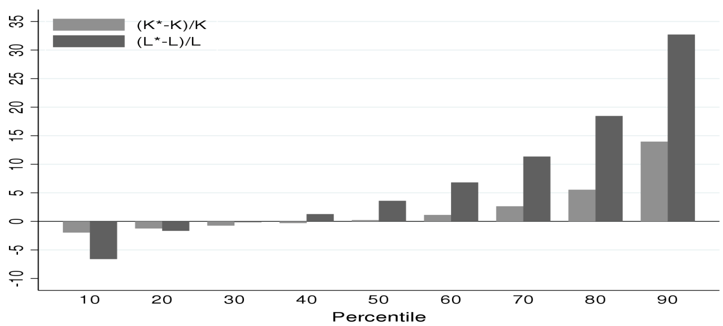
Figure 1.2. Distribution of percentage deviations from target capital, labor, and output

Panel a presents the distribution of MRP-cost gaps of labor τ_{it}^L and capital τ_{it}^K. Labor gaps are expressed in thousands of Euros; capital gaps in percentages. Panel b presents the distribution of percentage deviations from targets input demands $\left((K_{it}^*-K_{it})/K_{it}\right.$ and $\left.(L_{it}^*-L_{it})/L_{it}\right)$ and percentage deviations from output $\left((Y_{it}^*-Y_{it})/Y_{it}\right)$, both of which are expressed in percentages. In panel a and b the distribution is asset-weighted. In panel c we present both the unweighted and the asset-weighted distribution.

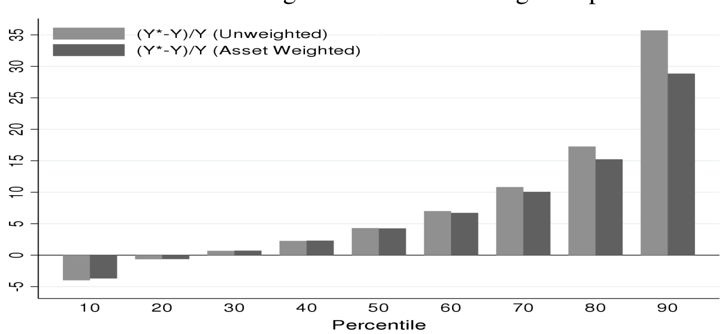
Panel a: MRP-cost gaps



Panel b: Percentage deviations from target input demands



Panel c: Percentage deviations from target output



According to our metric, the central percentiles of the distributions are occupied by firms whose capital and labor endowment appears to be relatively undistorted. The median gaps of capital and labor are 3.5% and 6 thousand euros for capital and labor, respectively.

Yet, the distributions of MRP-cost gaps are dispersed and highly right-skewed, reflecting the right-skewness of the corresponding distributions of marginal revenue products. In fact, the average capital and labor gaps are 37% and 9 thousand euros, respectively; the 90-10 percentile differences are almost 3 times larger.

Correlation with observable characteristics – The large dispersion in marginal revenue products could be entirely driven by measurement error or production function misspecification. Alternatively, as discussed in section 1.3, market frictions might distort the quantity of capital and labor employed by firms, and generate a dispersion of marginal revenue products above and beyond the variation observed in user costs. The correlation between MRP-gaps with firms' observable characteristics provides preliminary evidence in this direction.

We regress gaps on life cycle variables (firm age and size), credit score, measures of productivity and profitability (TFPR and ROA), and proxies of internal and external financing (cash-over-assets and bank leverage, respectively).[56] We focus on within-year and within-industry variation by controlling for year and industry fixed effects. Table 1.4 reports the regression results: panel a for capital and panel b for labor. Because τ^K and τ^L have different variability, coefficients are express as Z-scores to facilitate their comparison across the two panels.

MRP-cost gaps of capital monotonically decrease with firm age and size. In contrast, labor gaps are higher for larger and older firms. The availability of financing, either internally generated liquidity or bank debt, is negatively correlated with τ^K. Like capital gaps,

56. Age groups are defined as follows: young if age$\leq$ 5, medium if age$\in$ (10], old if age>10. Assets groups are defined based on the terciles of the distribution of assets (average assets across firms in each tercile are 190 thousand, 760 thousand, and 8.8 million Euros, respectively). Credit score groups are defined as follows: safe firms are those with a credit score ranging from "Excellent" to "Solvent" (credit score from 1 to 4); a second group includes firms classified as "Vulnerable" and "Very vulnerable" (credit score from 5 and 6); Risky are firms with credit score ranging from "Risky" to "Very very risky" (credit score from 7 and 9).

Table 1.4: MRP-Cost gaps and firm's characteristics

This table reports the correlation between MRP-cost gaps and firm characteristics. Panel a focuses on the MRP-cost gap of capital (τ^K) and panel b on the MRP-cost gap of labor (τ^L). We regress gaps on life cycle variables (firm age and size), credit score, measures of productivity and profitability (TFPR and ROA), and proxies of internal and external financing (cash-over-assets and bank leverage, respectively). Age groups are defined as follows: young if age$\leq$ 5, medium if age$\in$ (10], old if age>10. Assets groups are defined based on the terciles of the distribution of assets (average assets across firms in each tercile are 190 thousand, 760 thousand, and 8.8 million Euros). Credit score groups are defined as follows: safe firms are those with a credit score ranging from "Excellent" to "Solvent" (credit score from 1 to 4); a second group includes firms classified as "Vulnerable" and "Very vulnerable" (credit score from 5 and 6); Risky are firms with credit score ranging from "Risky" to "Very very risky" (credit score from 7 and 9). We focus on within-year and within-industry variation by controlling for year and industry fixed effects. All variables in the regressions are standardized so that coefficients are express as Z-scores. Standard errors (in parenthesis) are clustered at the firm level.

Panel a: MRP-Cost gap of capital (τ^K_{it})

Age		Credit Score		TFPR
Young	Omitted Category	Safe	Omitted Category	0.411 (0.004)***
Medium	-0.273 (0.002)***	Vulnerable	0.019 (0.002)***	
Old	-0.316 (0.002)***	Risky	-0.048 (0.002)***	ROA
				0.151 (0.003)***
Assets		Leverage		
Small	Omitted Category	-0.066 (0.001)***		
Medium	-0.077 (0.002)***			
Large	-0.116 (0.003)***	Cash / Assets		
		-0.193 (0.007)***		
Year Fixed Effects		Y		
Industry Fixed Effects		Y		
Adj. R^2		0.106		
R^2 Year and Industry FE only		0.049		
Observations		3511678		

Panel b: MRP-Cost gap of labor (τ^L_{it})

Age		Credit Score		TFPR
Young	Omitted Category	Safe	Omitted Category	0.798 (0.003)***
Medium	0.082 (0.002)***	Vulnerable	-0.011 (0.002)***	
Old	0.059 (0.002)***	Risky	-0.079 (0.002)***	ROA
				0.152 (0.001)***
Assets		Leverage		
Small	Omitted Category	0.0552 (0.001)***		
Medium	0.009 (0.002)***			
Large	0.382 (0.003)***	Cash / Assets		
		-.007 (0.001)***		
Year Fixed Effects		Y		
Industry Fixed Effects		Y		
Adj. R^2		0.292		
R^2 Year and Industry FE only		0.128		
Observations		3863961		

labor gaps are lower for firms with high cash flows but, unlike capital gaps, they increase with bank leverage.

MRP-cost gaps are low for firms with poor credit scores. For capital, this relation is non-linear, and it is driven by a combination of lower marginal revenue products and higher interest rates charged by banks. For labor, the negative correlation is entirely driven by the variation in marginal products of labor, while wages display little sensibility and, if anything, they tend to be lower for firms with poor credit scores.

The relation between both capital and labor gaps and productivity and ROA is positive and economically relevant, suggesting that higher MRP-cost gaps might capture unexpressed growth potentials.

One interpretation of these patterns is that firms tend to substitute labor inputs for capital inputs as they grow older and bigger. On the one hand, labor is more costly for larger firms than for smaller ones due to the size-dependent provisions of the Italian employment protection regulation (see section 1.2). On the other hand, access to external finance is more expensive and possibly constrained in early stages of firms' life cycle ([67]). Alternatively, it is possible that younger and smaller firms might hold on to partially irreversible capital investments because they face a more volatile demand ([23]). Larger capital gaps for young and small firms might also be the results of a form of non-classical error in the measurement capital that decreases with firm size and age. In the next section, we construct empirical tests that allow us to investigate to what extent the sign and magnitude of MRP-cost gaps reflect the degree of financial constraints and labor market rigidities faced by individual firms.

1.5 MRP-cost Gaps and Market Frictions

This section presents empirical evidence of the relationship between MRP-cost gaps and credit and labor market frictions. On the capital side, we analyze the impact of asymmetric information in credit markets, investigate the relationship to bankruptcy costs, test the response of MRP-cost gaps to credit-supply shocks, and study the dynamic of the capital gap as firms transition into the credit market. On the labor side, we show the relationship between MRP-cost gaps of labor and labor market frictions by analyzing the impact of the size-dependent severance payment requirements on firms' employment policies.

1.5.1 Credit Market Distortions

1.5.1.1 Information Frictions

Theory suggests repeated interactions with financial intermediaries allow firms to overcome possible asymmetric-information frictions, and gradually accumulate a capital endowment more consistent with profit maximization ([110]). Enduring bank-firm relations typically translate into a reduction in the expected costs of credit provision for lenders, because, conditional on past experience with the borrower, the lender now expects loans to be less risky ([14]; [56]). Moreover, besides the effect on the probability of default, monitoring and screening costs related to information acquisition are generally lower for existing customers, because information obtained at one date may also be used to assess risk at a later date. The discussion in section 1.3 highlights that lenders could respond to a decline in the expected cost of credit provision by adjusting the price term of the loan contract or by relaxing credit limits that might be in place. We provide empirical evidence in favor of the latter, and show that firm-level MRP-cost gaps for capital can be used to study the impact of asymmetric information on capital accumulation by firms.

Price versus quantity adjustments – We begin by analyzing the relationship between probability of default and the duration of lending relationships. We focus on the subsample of observations that engage in credit markets transactions and for which we have information on borrowing rates (see section 1.4.1).

We define the dummy variable DEFAULT_{t+1} that takes the value of 1 in year t when we observe in year $t+1$ any credit in default, or any debt restructured, or in the process of being restructured.[57] Then, we estimate the following linear model:

$$\text{Default}_{it+1} = \beta_1 \cdot \text{Length Relation}_{it}^{wmean} + \Gamma X_{it} + \iota_{spt} + \varepsilon_{it}\,. \tag{1.5}$$

To claim that longer lending relationships are less likely to culminate in default events, we must control for the underlying local credit market conditions, as well as loan- and firm-specific characteristics that are related to the strength of consumers' demand and might affect firm profitability and credit risk. Thus, the empirical model includes year-by-province-by-industry dummies and a vector of firm-specific characteristics (X_{it}) that includes firm-level productivity (ω_{it}), assets turnover, ROA, cash flows over assets, current bank leverage (bank debt/assets), nine dummy variables corresponding to each value taken by the Altman Z-score, and decile dummies for firm age and size.[58] As discussed in section 1.4.1, these variables are a set of observable indicators commonly used by banks to assess firms' riskiness and creditworthiness. We also control for the number of active credit relations to account for heterogeneity in the intensity of credit market participation.

57. This definition is similar to the one adopted by [111] and [57]. The unconditional probability of default is 2.6% among firms in the regression sample.

58. In the baseline regressions, we use 2-digits industries for the construction of year-by-province-by-industry dummies. This choice allows us to control for fairly granular industry heterogeneity while avoiding a reduction in the sample size due to singleton observations once we interact industry, year, and provinces. This choice does not affect our results. In fact, using more (4-digits industries) or less restrictive (macro industries) definition of industries, coefficients remain remarkably stable.

Conforming with the prediction of economic theory, we find a negative correlation between default and length of lending (Table 1.5, column (1)).

Next, we investigate if, and to what extent, the reduction in credit is passed through a reduction of the interest rates or, rather, through a relaxation of existing credit-supply constraints. We estimate the regression model in equation (1.5) using borrowing rates and MRP^K as a left-hand-side variable. Despite the incidence of productivity on default rates, the data show a relative insensitivity of borrowing rates to the duration of lending relations. Conditional on bank leverage and other observable characteristics, one extra year of lending relationships reduces interest rates by 2 basis points (Table 1.5, column (2)). Instead, the length of lending relationships is strongly and negatively associated with MRP^K (column (3)). Comparing two observationally similar firms that differ by one year in terms of length of lending relationships, the firm with the shorter relationship displays a marginal revenue product of capital 138 basis points higher.

The relationship between interest rates and MRP^K with the length of lending relationships is consistent with the predictions of theories of credit rationing ([11]; [12]). Lacking complete information about their clients, lenders are reluctant to adjust the price of credit, because such adjustment affects both the composition of the borrowing pool and their borrowing behavior. Credit limits - rather than credit prices - adjust as bank-firm relations unfold and more information is acquired ([112] [112] [113], [114]; [56]; [115]), and the MRP^K drops as profitable investments are undertaken.[59]

Another explanation is lack of competition in credit markets. If information about a firm's creditworthiness is difficult to acquire and not easily transferable, relationship lend-

59. The stickiness of interest rates and the importance of credit limits as the primary margin of adjustment of credit contracts has been also shown in the market for credit cards (see [54] and references cited). Other types of non-price adjustments of the terms of credit contracts have been documented in other consumer credit markets, for example, the downpayment requirements for subprime auto loans in [52] and [53].

Table 1.5: Information frictions and relationship lending

This table explores the relation between length of lending relationships (LENGTH RELATION$_{it}{}^{wmean}$) and borrowing rates (r_{t+1}), marginal revenue products of Capital (MRP^K_{it+1}), and MRP-cost gaps of capital (τ^K_{it}). In Panel a, firm-level controls include: age and size dummies (deciles), credit score dummies (9 values), assets turnover, ROA, cash flows over assets, leverage, and the number of active credit relationships. These regressions include year by province by industry (2-digits industry codes) fixed effects. In Panel b we augment the specification with firm fixed effects, and replace age and size deciles with a second order polynomial in age and lag of log assets. Columns (5)–(7) in Panel a and Columns (2)–(4) in Panel b, also include the interactions of all variables and fixed effects with UNDERCAPITALIZED$_{t-1}$(=1 if $\tau^K_{it-1} > 0$), TFPR$_t$ (mean-zero ω_{it}), and UNDERCAPITALIZED$_{t-1}$x TFPR$_t$. Regressions are run on the sub-sample of borrowers with outstanding loans for which we observe the APR on loans. Standard errors (in parenthesis) are clustered at the firm level.

Panel a: Between Firm Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$Default_{it+1}$	r_{t+1}	MRP^K_{t+1}	$\lvert\tau^K_t\rvert$		τ^K_t	
LENGTH RELATION$^{wmean}{}_t$	-0.001	-0.020	-1.138	-0.936	-0.029	-2.273	-0.019
	(0.000)∗∗∗	(0.001)∗∗∗	(0.060)∗∗∗	(0.052)∗∗∗	(0.011)∗∗∗	(0.048)***	(0.012)*
LENGTH RELATION$^{wmean}{}_t$ x UNDERCAPITALIZED$_{t-1}$					-0.851		-0.744
					(0.092)∗∗∗		(0.091)∗∗∗
LENGTH RELATION$^{wmean}{}_t$ x TFPR$_t$						-1.215	0.097
						(0.130)∗∗∗	(0.029)∗∗∗
LENGTH RELATION$^{wmean}{}_t$ x UNDERCAPITALIZED$_{t-1}$x TFPR$_t$							-2.962
							(0.199)∗∗∗
TFPR$_t$	-0.027	0.036	36.998	30.355			
	(0.002)∗∗∗	(0.009)∗∗∗	(0.860)∗∗∗	(0.757)∗∗∗			
ASSETS TURNOVER$_t$	-0.004	0.044	23.495	16.924			
	(0.001)∗∗∗	(0.003)∗∗∗	(0.371)∗∗∗	(0.306)∗∗∗			
ROA$_t$	-0.141	1.288	114.577	85.482			
	(0.003)∗∗∗	(0.038)∗∗∗	(4.629)∗∗∗	(3.660)∗∗∗			
CASH FLOWS$_t$/ ASSETS$_t$	-0.008	-0.933	-131.025	-102.490			
	(0.002)∗∗∗	(0.051)∗∗∗	(7.382)∗∗∗	(5.781)∗∗∗			
BANK LEVERAGE$_t$	-0.004	-0.565	-8.774	-6.843			
	(0.000)∗∗∗	(0.005)∗∗∗	(0.418)∗∗∗	(0.362)∗∗∗			
NUMBER RELATIONS$_t$	0.004	0.027	-0.496	-0.610			
	(0.000)∗∗∗	(0.001)∗∗∗	(0.067)∗∗∗	(0.059)∗∗∗			
FIRM CONTROLS	-	-	-	-	Y	Y	Y
AGE, SIZE, CREDIT SCORE FE	Y	Y	Y	Y	Y	Y	Y
INDUSTRY X YEAR X PROVINCE FE	Y	Y	Y	Y	Y	Y	Y
YEAR FE	N	N	N	N	N	Y	N
FIRM FE	N	N	N	N	N	N	N
ADJ. R2	0.146	0.486	0.114	0.093	0.167	0.070	0.167
OBS.	1887314	1887314	1887314	1887314	1633484	1633697	1633484

Panel b: Within Firm Regressions

	(1)	(2)	(3)	(4)
	$\lvert\tau^K_t\rvert$		τ^K_t	
LENGTH RELATION$^{wmean}{}_t$	-1.489	-0.473	-0.476	-0.462
	(0.053)∗∗∗	(0.033)∗∗∗	(0.046)∗∗∗	(0.034)∗∗∗
LENGTH RELATION$^{wmean}{}_t$ x UNDERCAPITALIZED$_{t-1}$		-0.509		-0.462
		(0.061)∗∗∗		(0.061)∗∗∗
LENGTH RELATION$^{wmean}{}_t$ x TFPR$_{t-1}$			-0.685	0.031
			(0.111)∗∗∗	(0.051)
LENGTH RELATION$^{wmean}{}_t$ x UNDERCAPITALIZED$_{t-1}$x TFPR$_t$				-1.568
				(0.132)∗∗∗
FIRM CONTROLS	Y	Y	Y	Y
AGE, SIZE, CREDIT SCORE FE	Y	Y	Y	Y
INDUSTRY X YEAR X PROVINCE FE	Y	Y	Y	Y
YEAR FE	N	N	Y	N
FIRM FE	N	N	N	N
ADJ. R2	0.575	0.638	0.624	0.639
OBS.	1846643	1614149	1614591	1614149

ing gives current lenders monopoly power over other intermediaries, which allows them to extract rents from highly productive firms they manage to "lock-in" ([116]; [87]).[60] In Appendix A.9.1 we test to what extent the relation between the length of lending relationships, interest rates, and marginal revenue products is a function of the degree of competition of credit markets ([116]; [87]). Interest rates are higher and the correlation between interest rates and the length of lending relations is less negative in more concentrated markets. Both predictions are in line with the imperfect competition hypothesis. Interestingly, the correlation between Marginal Products of capital and the length of lending relationships is also less negative in more concentrated markets. However, the effect of duration on marginal revenue products of capital swamps the variation in interest rates regardless of the degree of credit market competition.

Before examining the relation between MRP-cost gaps and the length of lending relationships, we highlight an additional piece of empirical evidence in line with the asymmetric information hypothesis that comes from the relation between productivity, defaults, and interest rates. In frictionless credit markets, theory predicts a negative correlation between firm-specific productivity and the cost of debt. In the model of Appendix A.3 we show that, under an efficient risk classification system and frictionless credit markets, high-productivity firms are safer customers from a bank's perspective because, *ceteris paribus*, they are less likely to default on their debt obligations. Column (1) shows that, conforming with these theoretical predictions, more productive firms are indeed less likely to default on their credit obligations. Ceteris paribus, one interquartile range difference in TFPR (0.41 in the subsample of borrowers with loans) is associated with a reduction of the observed probability of default of 1.2 percentage points. This effect is economically significant, con-

60. See [117], [118], and [119] for a theoretical treatment on the link between credit market competition, information acquisition incentives, and credit-supply.

sidering that the unconditional probability of default is 2.6% among firms in the regression sample.

Yet despite the incidence of productivity on default rates, the data provide weak support for the proposition that interest rates vary with firm-level productivity. In fact, we find a positive correlation between productivity and borrowing costs. This effect is statistically significant but economically negligible: all else being equal, one interquartile range difference in TFPR ω is associated with a 3.6 basis points increase in the observed interest rate (less than 2% of a standard deviation in borrowing rates). These results suggest productivity may not belong to the variables in banks' pricing kernel, possibly because it is unobservable to banks, and that the positive coefficient is a reflection of more productive firms' greater willingness to pay.[61] Imperfect competition ("lock-in" hypothesis) might also explain the relation between the two variables. However, as we show in Appendix A.9.1, we find no economically significant response of borrowing rates to productivity, irrespective of the degree of credit market concentration.[62]

Length of lending relationships and MRP-cost gaps – Given the sluggish response of interest rates and much larger sensitivity of MRPK, we expect to find a strong relation between MRP-cost gaps of capital and the variable $\text{LENGTH RELATION}_{it}^{wmean}$. Figure 1.3 (panel a) shows that indeed this is the case. With respect to the year in which relationships

61. An econometric explanation of this result would be that our estimates of productivity have no empirical content, due to measurement and/or misspecification errors. Prima facie, this explanation seems implausible. Our estimates of TFPR are highly correlated with credit-default outcomes and, as we show in Appendix A.4, both investment rates and changes in labor demand are closely related to productivity dynamics, as theory would predict.

62. A possible explanation for this result is that competition among credit suppliers works to eliminate systematic misclassifications due to imperfect information. For example, if a firm is - by mistake - classified as excessively risky or not creditworthy by one lender, competitive lenders may offer a lower interest rate to attract that customer.

are established, the gap τ^K is 2 times (3 times) lower after 3 years (6 years) of continuous interactions.

Figure 1.3. MRP-cost gaps of capital and length of lending relations

This figure displays the relation between MRP-cost gaps of capital (τ_{it}^K) and the length of lending relationships (LENGTH RELATION$_{it}^{wmean}$). Panel a displays the raw correlation. Panels b, c, and d plot the regression coefficients associated with dummy variables indicating different length of lending relationships (omitted category: LENGTH RELATION$_{it}^{wmean}$$\leq$0.5 years). The regression model includes firm-level controls and industry by province by year fixed effects. In panel c, undercapitalized firms are those with $\tau_{it-1}^K > 0$. In panel d, high-TFPR firms are those with TFPR above the median of the distribution of TFPR (ω_{it}). All quantities on the y-axis are expressed in percentages. The length of relationships is expressed in years.

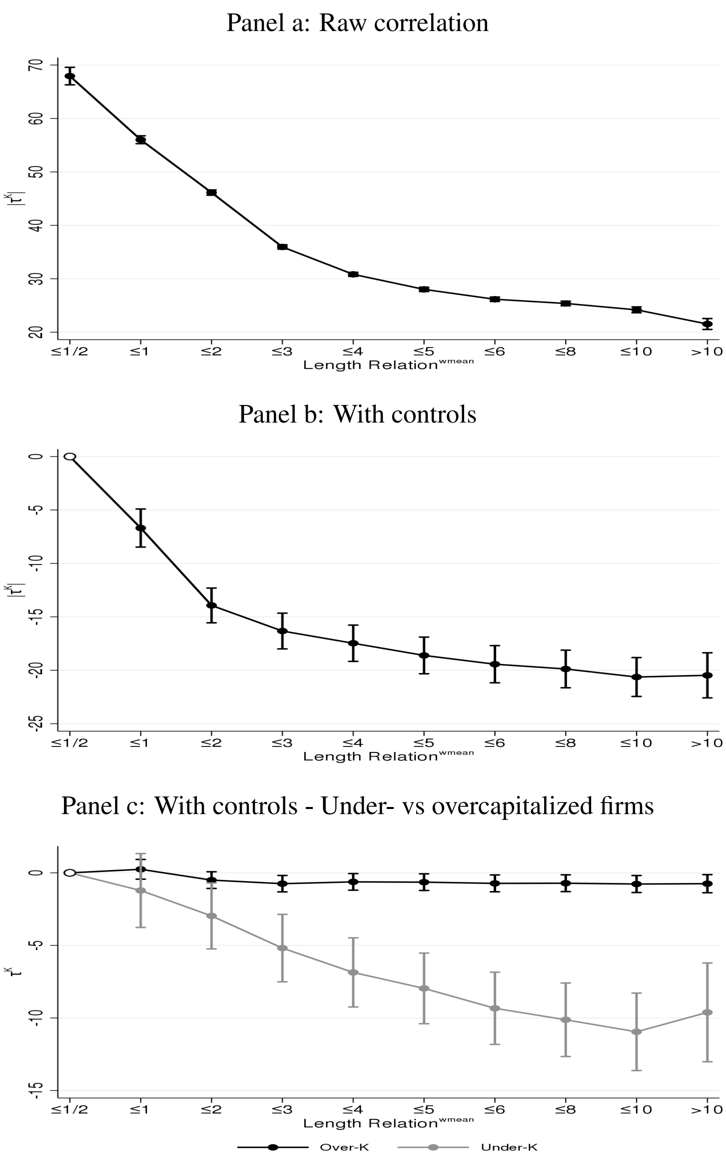
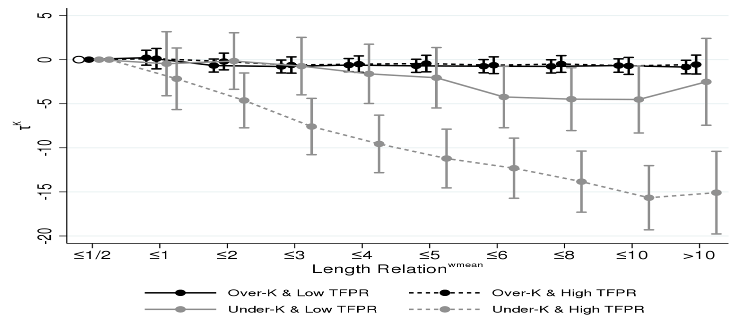


Figure 1.4. Figure 1.3 (cont'ed): MRP-cost gaps of capital and length of lending relations

Panel d: With controls - Productivity



This descriptive analysis suggests a remarkably strong association between the two variables, yet other confounding factors might explain this pattern. We turn to regression analysis to try to isolate the effect of a relaxation of information frictions from alternative explanations. We estimate the following regression model:

$$\tau^K{}_{it} = \beta_1 \cdot \omega_{it} + \beta_2 \cdot \text{Length Relation}_{it}^{wmean} + \Gamma X_{it} + \iota_{spt} + \varepsilon_{it}\,. \tag{1.6}$$

The vector X_{it} includes TFPR, ROA, cash-flow-to-assets ratio, assets turnover, leverage, credit score dummies, the number of active credit relationships, and a battery of age and size fixed effects (decile dummies). By controlling for TFPR and profitability measures, and by restricting our analysis to variation within industry-year-province bins (ι_{spt}), we tackle the concern that the dispersion in the realized MRP-cost gaps is driven by idiosyncratic variation in investment opportunities, industry-specific demand shocks ([7]), or time-varying risk premia.[63] The flexible controls for age and size are also crucial. As [23] point out, young and small firms face a more volatile demand that might discourage them

63. In the baseline regressions, we use 2-digit industries for the construction of year-by-province-by-industry dummies. This choice does not affect our results. In fact, using a more (4-digit industries) or less restrictive (macro industries) definition of industries, the coefficients remain remarkably stable. We also experimented with replacing the vector of contemporaneous controls with its lagged counterpart. Results are unchanged. Results are available upon request.

from undertaking partially irreversible investments, regardless of the cost and availability of external financing.

Regression results are reported in Table 1.5, Panel a. Column (1) shows that MRP-cost gaps strongly correlate with the average length of lending relationships between a bank and its lenders. Net of the variation explained by firm characteristics and local market dynamics, longer lending relationships allow firms to gradually implement more efficient investment policies. Ceteris paribus, one additional year of continuous borrower-lenders interactions is associated with a reduction in the *absolute value* of MRP-cost gaps of capital by about 98 basis points. We estimate model (1.6), replacing the continuous variable LENGTH RELATION$_{it}^{wmean}$ with a set of dummy variables. Figure 1.3, Panel b, plots the regression coefficients associated with each dummy variable (LENGTH RELATION$_{it}^{wmean} \leq 1/2$ is the baseline category, which is omitted in the regression). It shows that the monotonic relation between the two variables holds across the entire distribution of LENGTH RELATION$_{it}^{wmean}$. Examining the control variables, we find τ^K is positively related to measures of profitability (productivity, ROA, and assets turnover). This finding is consistent with the interpretation that a positive gap between the MRP-cost gap τ^K signals potential investment opportunities. The analysis of the coefficients of age and size - not reported in the regression table - shows that, as expected, gaps are smaller for older and larger firms. The relation between MRP-cost gaps and credit scores is non-monotonic: everything else being equal, τ^K increases as we move from firms with high credit rating to firms with intermediate ratings (Altman Z-score from 1 to 5) , and then τ^K sharply drops once we consider firms with the lowest credit ratings (Altman Z-score from 6 to 9). The negative sign of the coefficient associated with the number of active credit relations is also in line with our interpretation, because a larger pool of lenders provides firms with a greater set of financing options. Gaps are also negatively related to the availability of internal and external finance, as the coefficients of cash flows and leverage indicate.[64]

Heterogeneous effects – The average effect, however, masks substantial heterogeneity across producers. In column (2), we interact the length of the lending relationships with a dummy variable that indicates whether the firm was operating below its target capital endowment in period $t-1$ ($\text{UNDERCAPITALIZED}_{it-1} = \mathbf{1}\{\tau^K_{it-1} > 0\}$), as well as a the full set of interactions of the dummy $\text{UNDERCAPITALIZED}_{it-1}$ with the vector of controls and fixed effects in the regression model (1.6).[65] Consistent with MRP-cost gaps being proportional to the shadow cost of capital, we find that the economic benefits of longer credit relations are almost entirely concentrated among under-capitalized producers, helping them overcome potential information frictions that constrained the availability of bank finance. Figure 1.3, Panel c, shows this point clearly by showing the effect of longer relationships for $\text{UNDERCAPITALIZED}_{it-1} = \{0,1\}$, across the distribution of $\text{LENGTH RELATION}^{wmean}_{it}$. We find a negligible impact of longer lending relationships on the MRP-cost gap of firms that operate with a capital endowment that, according to our measure, exceeds the one more consistent with unconstrained profit maximization. Despite its small magnitude, the negative sign of the coefficient on $\text{LENGTH RELATION}^{wmean}_{it}$ suggests longer relationships might actually allow some overcapitalized firms to maintain, or even increase their capital endowment.

Another testable implication of the theory of gaps is the relation to firm-level productivity. As discussed in section 1.3, theory suggests the MRP-cost τ^K is proportional to the multiplier attached to the borrowing constraint (χ_{it}). The shadow cost of capital χ_{it}

64. We observe a statistically significant, positive relation between the length of lending relations and bank leverage. On average, one more year of lending relationships is associated with a 5% increase in bank leverage (p-value lower than 1%).

65. The full regression table is available upon request.

is increasing with the firm's productivity because, ceteris paribus, more productive firms are capable of transforming one extra unit of capital into more revenues. Thus, if variation in τ^K truly reflects heterogeneous shadow costs due to binding financial constraints, the benefits of bank-firm interactions should be larger for more productive firms that appear to be undercapitalized. These theoretical predictions find strong empirical support. We augment the model with the interaction between TFPR (ω_{it}) and the length of lending relationships (column (3)), and the triple interaction with UNDERCAPITALIZED$_{it-1}$ (column (4)). To facilitate the interpretation of estimates, we de-mean ω_{it}, so that the coefficient associated with LENGTH RELATION$_{it}^{wmean}$ represents the average response of τ^K to one additional year of firm-bank interactions for a firm located at the mean of the distribution of TFPR. In column (4), the same coefficient refers to an overcapitalized firm located at the mean of the distribution of TFPR. We find a stronger correlation between gaps and the length of lending relationships for more productive firms. In particular, the sign and magnitude of the coefficient associated with the triple interaction (LENGTH RELATION$_{it}^{wmean}$ x UNDERCAPITALIZED$_{it-1}$ x TFPR$_{it}$) shows that the benefits of relationship lending accrue, for the most part, to the subsample of the most productive firms that operate with too little capital. Figure 1.3 (Panel d) provides a visual representation of the heterogeneous effects of longer lending relationships along the productivity spectrum.[66]

Robustness – We augment the regression model with firm fixed effects, and study the impact of a relaxation of borrower-lender information frictions over the firm' life cycle (Table 1.5, Panel b). By doing so, we strengthen the identification of the coefficient of interest, because we now control for time-invariant unobservable firm characteristics and we also better address measurement error problems. The within-firm estimates largely confirm the

66. In the graph, the variable HIGH-TFPR$_{it}$ that takes value of 1 for observations whose productivity is above the median, and zero otherwise.

results of the between-firm regressions. Also, Appendix A.9 shows results are qualitatively similar if we measure the degree of information frictions using the unweighted average length of relations ($\text{Length Relation}_{it}^{mean}$), or using only the length of the relation with the main lender ($\text{Length Relation}_{it}^{lead}$).

1.5.1.2 Bankruptcy costs

Next, we investigate the relationship of MRP-cost gaps and bankruptcy costs. Inefficient bankruptcy procedures have an unambiguous, detrimental effect on firm activity. On the one hand, higher bankruptcy costs might affect investments because interest rates rise, which reduces the credit demand. On the one hand, when the cost of credit is inflexible or only partially adjusts, bankruptcy costs affect investment through a reduction of the availability of external finance (lower λ, through the lens of our theoretical model), which, as we previously discuss, would raise the marginal revenue product of capital of credit constrained firms.

We test these alternative hypotheses using the length of bankruptcy litigations in court as an empirical proxy of the deadweight cost of bankruptcy. The length of the bankruptcy procedures increases the deadweight loss in case of bankruptcy for several reasons.[67] First, long trials increase legal expenses, and for disputed loans, interest income is forgone when collateral does not cover judicial costs. Second, during the trial, the creditor is exposed to the danger of asset substitution by the debtor. Third, even in the absence of moral hazard behaviors, the market value of firm assets typically decays during the period of automatic stay. The average length of judicial proceedings across different court jurisdictions displays

67. The seminal work of [120] ([120]; [121]) highlights that law and its enforcement by the judiciary are essential to credit markets. [122] provide empirical evidence of the impact of costs associated with inefficient debt enforcement procedures. [123] and [124] show how legal differences shape the ownership and terms of bank contracts. A body of empirical works investigate the connections between legal institutions and firm size (e.g., [125]).

Table 1.6: Bankruptcy costs

This table explores the relation between bankruptcy costs (LENGTH BANKRUPTCY) and borrowing rates (r_{t+1}), marginal revenue products of Capital (MRP^K_{it+1}), and MRP-cost gaps of capital (τ^K_{it}). Firm-level controls in include: age and size dummies (deciles), credit score dummies (9 values), assets turnover, ROA, cash flows over assets, leverage, weighted average length of lending relationships, and the number of active credit relationships. Province-level controls, measured in 2007, include: population, GDP, unemployment rate, active firms per resident, firm exit rate, Herfindahl-Hirschman Index of credit market concentration, and the number of active credit institutions. Columns (1)–(3) include year by industry fixed effects. Columns (8) and (9) include year by industry by macro-region (North, Center, South of Italy) fixed effects. Regressions are run on the sub-sample of borrowers with outstanding loans for which we observe the APR on loans. Standard errors (in parenthesis) are clustered at the firm level.

	(1)	(2)	(3)	(4)	(5)	(6)
	r_{t+1}	MRP^K_{t+1}	τ^K_t	r_{t+1}	MRP^K_{t+1}	τ^K_t
LENGTH BANKRUPTCY	0.013	0.423	0.363	0.003	0.208	0.181
	(0.001)***	(0.086)***	(0.077)***	(0.001)**	(0.088)**	(0.079)**
FIRM CONTROLS	Y	Y	Y	Y	Y	Y
PROVINCE CONTROLS	Y	Y	Y	Y	Y	Y
INDUSTRY X PROVINCE FE	Y	Y	Y	N	N	N
INDUSTRY X YEAR X M. REGION FE	N	N	N	Y	Y	Y
ADJ. R2	0.468	0.113	0.110	0.471	0.114	0.111
OBS.	1822631	1822631	1822631	1822618	1822618	1822618

significant geographical variation (see Figure A.1, Panel a, in the Appendix). The between-province standard deviation is two years, with judgments taking "as little as" three years to become final in some provinces, but as much as 13 years in others.

We augment the regression model (1.6) with the length of bankruptcy cases (LENGTH BANKRUPTCY) and investigate its covariance with borrowing costs, MRP^K, and the gap τ^K. Because the bankruptcy variable is fixed over time, we cannot include industry-year-province fixed-effects, which we replace with industry-year fixed-effects plus a rich set of province-level controls (population, GDP, unemployment rate, active firms per resident, firm exit rate, Herfindahl-Hirschman Index (HHI) of credit market concentration, and number of active credit institutions).

Results show that borrowing costs are only marginally affected by heterogeneous bankruptcy costs, whereas MRP^K responds markedly (Columns (1) and (2) of Table 1.6). Consistent with bankruptcy costs generating more severe credit constraints rather than higher borrowing rates, we find that, on average, one extra year of legal controversies increase the Marginal Product of Capital by 42 basis points but increases the interest rate by 0.9 basis points. These results are in line with [126], who finds that judicial efficiency in Italy correlates positively with the volume of lending and negatively with proxies for credit constraints. Given the small sensitivity of borrowing rates and significant response of MRP^K, it follows that inefficiencies in the legal system translate into larger MRP-cost gaps. Comparing similar firms that operate in the same industry-year, we find that one extra year of bankruptcy litigations in court translates into an average increase of 37 basis points in τ_{it}^K.

We worry that the coefficient associated with the length of bankruptcy litigations might be simply picking up the stark difference in the quality of institutions or in the level of human and social capital between the northern and the southern regions of the country ([27]; [16]; [16]). In fact, bankruptcy litigations are, on average, two years longer in the South than in the rest of the country. In column (10), we focus on within macro-region variation to try to disentangle the effect of bankruptcy costs from the North-South effect.[68] As expected, year-by-industry-by-macro region fixed effects reduce the correlation of bankruptcy length with both interest rates and marginal revenue products of capital, but the differential effect of LENGTH BANKRUPTCY on the two variables becomes even stronger. The correlation coefficient between bankruptcy costs and τ^K also shrinks. However, the relationship between the two variables remains statistically relevant.

1.5.1.3 Credit availability

The analysis presented so far uses the length of lending relationships and bankruptcy costs as proxies of the supply of credit available to individual firms, providing indirect evidence of the impact of credit availability on the size and dispersion of MRP-cost gaps. We now estimate the direct effect of credit supply on MRP-cost gaps of capital. We start from the

68. Significant variation exists in the length of bankruptcy cases within macro-regions (Figure A.1, Panel b): the standard deviation between macro-regions is 1.11 years, and the average standard deviation within-region is 1.93 years.

spurious correlation between changes in credit amounts granted and changes in τ^K. We estimate the following linear model:

$$\Delta\tau_{it}^{K} = \beta_1 \cdot g(Credit_{it}) + \Gamma X_{it-1} + \iota_{spt} + \varepsilon_{it}\,, \tag{1.7}$$

where $g(Credit_{it}) = (Credit_{it} - Credit_{it-1})/0.5 \cdot (Credit_{it} + Credit_{it-1})$ is the symmetric growth rate of bank credit ([127]). With respect to $\Delta ln(Credit_{it})$, this growth rate has the advantage of being defined also for firms that stop borrowing ($Credit_{it} = 0$) and, being bounded between -2 and +2, it is more robust to the presence of outliers. The vector X_{it-1} is the same set of firm-level controls of model (1.6), but measured in period $t-1$; ι_{spt} are industry-province-year fixed effects.[69] Results are reported in column (1) of Table 1.7. All else being equal, comparing two firms that face a one-standard-deviation difference in the firm-level growth rate of credit (37%), the MRP-cost gap τ^K of the firm with the greater growth rate of credit drops by 1.5 percentage points (-3.99*0.37).[70] Although suggestive, this correlation results from the simultaneous effect of firms' demand and banks' supply of credit. Thus, we cannot infer from OLS coefficients whether the variation in MRP-cost gaps reflects changes in the shadow cost of capital generated by constrained supply of credit, or rather heterogenous investment opportunities. To disentangle the demand and supply channels, we construct firm-year-specific credit-supply shifters adopting an empir-

69. The controls are assets turnover, ROA, cash-flow-to-assets ratio, leverage, credit score dummies, and the number of active credit relationships, length of lending relationships, age, age square, the natural logarithm of assets, and credit score dummies. We replicate our analysis using $\Delta ln(Credit_{it})$ as a left-hand side variable, and find estimates that are qualitatively and quantitatively very similar to the ones in Table 1.7. Regressions are available upon request.

70. In the estimation sample (borrowers in $t-1$ with information on APR on loans), the average change in firm-level credit is 4%, its standard deviation is 37%.

Table 1.7: Credit supply shifters

This table investigates the relationship between firm-specific credit-supply shocks and MRP-cost gap (τ_{it}^K). In Panel a, Column (1) reports the OLS coefficient; Column (2) and Column (3) the first stage regression, where the percentage change in credit (g(CREDIT$_{it}$)) is projected onto the credit supply shifter (CREDIT SHIFTER$_{it}$); Column (4) and Column (5) reports the reduced form regressions, where we project the gap onto the credit shifter. In Columns (6)-(8) regressions also include the interactions of all variables with UNDERCAPITALIZED$_{it-1}$(=1 if $\tau_{it-1}^K > 0$), TFPR$_{it-1}$ (mean-zero ω_{it-1}), and UNDERCAPITALIZED$_{it-1}$X TFPR$_{it-1}$. Columns (9) and (10) split the variation in the credit supply shifters in a positive changes (MAX{0,CREDIT SHIFTER$_{it}$}) and negative changes (MAX{0,-CREDIT SHIFTER$_{it}$}). In Column (10) we include the interactions of all variables with UNDERCAPITALIZED$_{it-1}$.

Panel b reports the Instrumental Variables (IV) regressions, where we instrument the percentage change in credit supply (g(CREDIT SHIFTER$_{it}$)) using the credit supply shifter. All regressions include 2-digit industry by year by province fixed effects and the following set of lagged controls: productivity (TFPR), the weighted average of the length of lending relationships, a second order polynomial in age, log assets, credit score dummies (9 values), assets turnover, ROA, cash flows over assets, leverage, and number of active credit relationships. In Columns (3)–(5) regressions also include the interactions of all variables with UNDERCAPITALIZED$_{it-1}$, TFPR$_{it-1}$, and UNDERCAPITALIZED$_{it-1}$X TFPR$_{it-1}$.

In Columns (3) and (5) in Panel a, and in Column (2) in Panel b, we include firm fixed effects. Regressions are run on the sub-sample of borrowers with outstanding loans for which we observe the APR on loans. Standard errors (in parenthesis) are clustered at the firm level.

Panel a: OLS, first stage, and reduced form regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	First Stage				Reduced Form			Reduced Form Positive VS Negative Shocks	
	$\Delta\tau_t^K$	g(CREDIT$_t$)				$\Delta\tau_t^K$			$\Delta\tau_t^K$	
g(CREDIT$_t$)	-4.173									
	(0.062)***									
CREDIT SHIFTER$_t$		0.209	0.246	-1.801	-1.512	-0.145	-2.373	-0.145		
		(0.003)***	(0.003)***	(0.149)***	(0.160)***	(0.054)	(0.152)***	(0.059)***		
CREDIT SHIFTER$_t$						-2.131		-2.019		
X UNDERCAPITALIZED$_{t-1}$						(0.261)***		(0.259)***		
CREDIT SHIFTER$_t$							-1.625	-0.008		
X TFPR$_{t-1}$							(0.361)***	(0.137)		
CREDIT SHIFTER$_t$								-1.501		
X UNDERCAPITALIZED$_{t-1}$X TFPR$_{t-1}$								(0.614)**		
MAX{0,CREDIT SHIFTER$_t$}									-3.101	-0.074
									(0.423)***	(0.159)
MAX{0,-CREDIT SHIFTER$_t$}									1.319	0.183
									(0.201)***	(0.074)**
MAX{0,CREDIT SHIFTER$_t$}										-4.293
X UNDERCAPITALIZED$_{t-1}$										(0.722)***
MAX{0,-CREDIT SHIFTER$_t$}										1.345
X UNDERCAPITALIZED$_{t-1}$										(0.359)***
FIRM CONTROLS	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
INDUSTRY X YEAR X PROVINCE FE	Y	Y	N	Y	N	Y	Y	Y	N	Y
YEAR FE	N	N	Y	N	Y	N	N	N	Y	N
FIRM FE	N	N	Y	N	Y	N	N	N	Y	N
ADJ. R2	0.059	0.189	0.307	0.055	0.126	0.096	0.065	0.096	0.055	0.095
OBS.	1610438	1610438	1578340	1610438	1578340	1595056	1610438	1595056	1610438	1595056

Table 1.7 (cont'ed): Credit supply shifters

Panel b: IV regressions

	(1)	(2)	(3)	(4)	(5)
			$\Delta\tau_t^K$		
g(CREDIT$_t$)	-8.581	-4.675	-0.722	-13.580	-0.733
	(0.713)***	(0.649)***	(0.272)***	(0.877)***	(0.305)**
g(CREDIT$_t$)			-10.015		-9.630
x UNDERCAPITALIZED$_{t-1}$			(1.234)***		(1.220)***
g(CREDIT$_t$)				-9.115	-0.093
x TFPR$_{t-1}$				(1.661)***	(0.699)
g(CREDIT$_t$)					-8.974
x UNDERCAPITALIZED$_{t-1}$x TFPR$_{t-1}$					(2.787)***
FIRM CONTROLS	Y	Y	Y	Y	Y
INDUSTRY X YEAR X PROVINCE FE	Y	N	Y	Y	Y
YEAR FE	N	Y	N	N	N
FIRM FE	N	Y	N	N	N
OBS.	1610438	1578340	1595056	1610438	1595056

ical design that is a variant of the shift-share approach of [18].[71] Specifically, using the bank-firm matched records of the CR, we decompose the yearly growth rate of credit at the relationship-level into a supply factor and demand factor using the following linear model:

$$g(Credit_{ibt}) = \mathbf{b}_{bt} + \mathbf{i}_{it} + e_{ibt}\,, \tag{1.8}$$

The left-hand side variable is the growth rate of credit from bank b to firm i, between year t and $t-1$. The vectors $\mathbf{b}_{bt}$ and $\mathbf{i}_{it}$ are bank-year and firm-year fixed effects. The regression is run via weighted least squares with weights equal to $Credit_{ibt-1}$. The coefficients of interest are the estimated bank-year fixed effects $\mathbf{b}_{bt}$. They capture the nationwide growth rate of credit of individual financial institutions, net of the overall change in lending that can be explained by firms' idiosyncratic demand, which is absorbed by the firm-year fixed effects $\mathbf{i}_{it}$. The identification of both $\mathbf{b}_{bt}$ and $\mathbf{i}_{pst}$ is guaranteed by the presence of multiple banks lending to the same firm at the same time (and banks lending to multiple firms). As discussed in section 1.2, the widespread presence of multi-bank firms ensures model (1.8) has enough power to accurately estimate the fixed effects of interest.[72]

Using the estimated bank-year fixed effects, we construct a firm-year-specific credit-supply shifter as

$$\text{Credit Shifter}_{it} = \sum s_{it-1}\hat{\mathbf{b}}_{bt}\,,$$

71. [17] propose a similar shift-share approach using more aggregated data. In Appendix A.10, we construct alternative credit supply shifters following their approach and find that our baseline results are very similar in terms of economic magnitude and statistical significance.

72. We run the regression on the full sample of firms that appear in the CR in order to maximize the representativeness of the sample and improve the precision of the estimates of the fixed effects. We exclude from the estimation sample the stock of loans in default. We deal with mergers and acquisitions, treating the acquired and acquiring bank as a single entity over the pair of years in which mergers and acquisitions take place ([128]). In the Italian Credit Registry, almost 70 percent of the firms borrow from multiple lenders during the same year, with an average number of 3.3 active lending relationships per year.

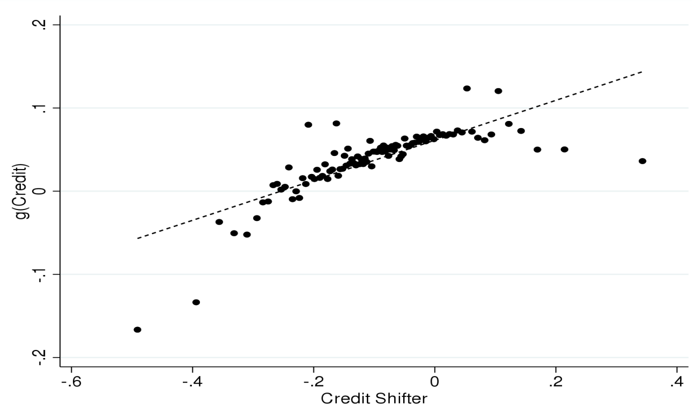
where $s_{ibt-1} = \frac{Credit_{ibt-1}}{\sum_b Credit_{ibt-1}}$ is the share of bank b on firm i total credit in period $t-1$. Appendix A.10 shows the distribution of Credit Shifter$_{it}$: the average and standard deviation are -10% and 13%, respectively.

In general, several factors create variation in the predicted credit-supply shifters, such as bank-specific events that affect the cost and availability of external financing of individual banks ([44]; [45]; [47]), shocks that weaken or strengthen bank balance sheets ([129]; [130]; [131]; [48]), banks heterogeneous response to monetary policy ([132]), or merger and acquisition events that might temporarily slow down or freeze the provision of credit ([133]). We take an agnostic view on what drives the change in credit for every individual bank. Below, we provide evidence of the information content of our estimated shifters showing their relation to banks' lending patterns during the recent European sovereign debt crisis.

We find an economically large and statistically strong relation between predicted supply shifters and growth rates of credit at the firm-level (Figure 1.5).

Figure 1.5. Relation between growth rates of credit and credit supply shifters

This figure shows the correlation between the growth rate of credit and the estimated credit supply shifters. A dot in the graph represents the average value of $g(\text{CREDIT}_{it})$ (y-axis) and the average value of CREDIT SHIFTER$_{it}$ (x-axis) across observations that belong to the same percentile of the distribution of CREDIT SHIFTER$_{it}$.



Column (2) of Table 1.7 (Panel a) examines this relationship more formally. The regression includes the battery of firm-level controls and fixed effects of model (1.7). Comparing two observationally similar firms that are exposed to a one-standard-deviation difference in the credit-supply shock, the firm facing the larger (positive) shock increases its bank debt by 2.7% more (0.21*13). Importantly, the coefficient of the correlation is remarkably stable and significant if we constrain the regression model to using only within-firm variation (column (3)). As we discuss below, these findings leave us confident that the predicted credit supply-shifters are not correlated with time-invariant borrowers' characteristics, including persistently high credit demand or investment opportunities.[73]

Reduced form estimates – Next, we use the predicted lending shocks to test the effect of changes in credit supply on τ^K_{it}. We find that gaps shrink in response to a supply-driven change in the availability of bank finance (Table column (4)). Ceteris paribus, one standard deviation difference in credit-supply shock is associated with a 0.24 percentage points reduction of the capital gaps (-1.88*0.13). The statistical relationship between the two variables holds true even if exploit only within-firm variation (column (5)).

Once again, the average effect masks the differential impact across firms that, before being exposed to the credit-supply shock, were operating with either an excessive or an insufficient capital endowment (column (6)). All else being equal, a one-standard-deviation difference in the credit-supply leads to a reduction of τ^K that is 11 times larger for under-capitalized ($\mathbf{1}\{\tau^K_{it-1} > 0\} = 1$) firms than for firms with zero or negative MRP-cost gaps

73. Although a formal test of the equality of the coefficients in column (2) and (3) rejects the null hypothesis with canonical statistical confidence levels, the change in magnitude is small in economic terms and small if compared to the change in the explained variance the inclusion of fixed effects brings about (adjusted R^2 increases by 11 percentage points). The increase in the coefficient from column (2) to column (3) does not appear to be driven by the reduction in sample size due to singleton observations in the firm-fixed effect regression. If we replicate model (3) on the estimation sample of model (4) we obtain a correlation coefficient of 0.208 (standard error 0.003). One interpretation of the larger correlation coefficient in column (3) is that unobserved time-invariant factors that affect credit growth at the firm-level are negatively correlated with credit-supply movements.

($\mathbf{1}\{\tau^K_{it-1} > 0\} = 0$, i.e., those that operate with a capital endowment close to or above target). The heterogeneous effect along the productivity margin is also economically relevant. We normalize the variable ω_{it-1} to have zero mean, and interact it with the credit shifter and with the dummy variable that flags firms with positive gaps in period $t-1$. Consistent with the analysis of the relation between capital gaps and the length of lending relationships, column (7) and (8) suggest the shadow cost of capital of more productive firms experiences a more pronounced drop compared to the drop in the shadow cost of capital of the less productive firms when hit by an equally large credit-supply shock, and that this effect is entirely driven by those producers our metric classifies as credit constrained.[74]

Finally, we study whether the response of MRP-cost gaps to positive changes in credit supply differs from the response to negative changes in credit supply, and whether this difference is across with positive or negative gaps (column (9) and (10). We find that change in gaps is substantial for capital-constrained firms, and especially in response to positive supply shocks. On the contrary, the MRP-cost gaps of firms with zero or negative MRP-cost gaps show an economically small response to negative credit shocks and no statistically significant response to positive ones. That is, by and large, this group of firms respond to an expansion in the credit supply by rolling over their debt, rather than by undertaking new investments, and does not appear to be affected by a credit contractions.

Identifying assumptions and robustness – The interpretation of the central result that variation in gaps is related to variation in credit constraints crucially depends on our ability to effectively disentangle credit supply movements from simultaneous changes in firms' idiosyncratic credit demand. One way to investigate the validity of our identification strategy is to study how the correlation coefficient between $g(Credit_{it})$ and $\text{C}\textsc{redit}\ \text{S}\textsc{hifter}_{it}$ and

74. In Column (8), the coefficient associated to Credit Shifter$_{it}$ measures the effect of a shifter of 100 percent on a firm with $\tau^K_{it-1} \leq 0$ and lagged TFPR equal to the average of ω_{it-1} in the estimation sample.

the model-explained variance change as we vary the set of firm-level controls and fixed effects in the regression model ([134]; [135]). We do so in Appendix A.10. If both the R^2 of the regression and the magnitude of the coefficient fluctuate substantially while changing the model specification, we would conclude that the correlation between firm-level changes in credit and our proxy of credit supply shifts might be the result of a spurious correlation of the two variables with local market conditions and firm characteristics. In contrast to this, we find that while the (adjusted) R^2 gradually increases as we augment the model with a larger set of fixed effects and controls (year fixed, province-by-industry-by-year fixed effects, firm-level controls, and firm fixed effects), the correlation coefficient between $g(Credit_{it})$ and $\text{C}\small{\text{REDIT}}\ \text{S}\small{\text{HIFTER}}_{it}$ remains remarkably stable across specifications.

Another important assumption needed to identify credit supply movements via model (1.8) is the absence of endogenous sorting between firms and banks. We provide two pieces of evidence that suggest that assortative matching is unlikely to be the sole driver of our results. First, if a systematic assortative matching is in place because good banks specialize in lending to fast-growing industries or local markets, we would see the coefficient of both the first-stage regression and of the reduced form regression change markedly as we control for more or less coarse industry fixed effects. Results provided in Appendix A.10 show the coefficient of interest is remarkably robust to model specification. Second, if bank-firm matching is persistent - as the duration of lending relationships seem to suggest -, firm fixed effects would control for it and possibly wipe out the statistical relation between credit supply and gaps. As previously discussed, including firm fixed effects in the regression does not erode the economic and statistical significance of the regression coefficients.[75] In Appendix A.10, we also experiment with alternative econometric models used to disentangle

75. Another assumption needed in the [18] methodology is the absence of spillover effects across supplies of different banks. This assumption seems to hold in the data: indeed, estimating the shifters controlling for these spillovers (i.e., by iterating several times estimates of bank-fixed effects, including past estimates of other banks into the decomposition) yields very similar credit-supply shocks ([19]).

simultaneous movements in supply and demand for credit at the firm level ([17]), and find estimates that are comparable in sign and magnitude to the ones in Table 1.7.

The firm-year fixed effects estimated by model (1.8) convey useful information about the demand for credit of individual firms ([48]). Thus, we use the estimated $\mathbf{i}_{it}$ to test two propositions. First, from a theoretical point of view, larger gaps should be a reflection of profitable investment opportunities not undertaken by firms. Thus, we expect to see a positive association between τ_{it-1} and the estimated firm-year fixed effects for year t. The data provide strong support in favor of this prediction, suggesting the larger gaps are associated with a greater demand for credit. Unconditionally, a one-standard-deviation increase in $\hat{\mathbf{i}}_{it}$ (0.47) is associated with a 6.6 percentage points larger τ_{it-1}. Second, we use $\hat{i}_{it}$ to verify that the estimated credit-supply shocks are in fact orthogonal with respect to firms' idiosyncratic credit demand. Including the estimated firm-year fixed effects $\hat{i}_{it}$ as a control, we fail to reject the hypothesis that the coefficient of the baseline regression of Table 1.7 (Panel b) is statically unchanged. Results of these tests are reported in Appendix A.10.

Our interpretation of the negative relation between gaps and credit availability is that constrained access to external finance prevents some firms from undertaking profit-maximizing investments. An alternative but related explanation is that gaps respond to credit-supply shocks because the latter affect firm-level productivity, which in turn affects the realization of MRP^K ([19]). In Appendix A.10, we show our results continue to hold controlling for the *simultaneous* change in productivity, which suggests that our estimates are driven by an efficient adjustment in the quantity of capital utilized by firms, rather than a possible increase in firm-level productivity.[76]

76. We fail to reject the hypothesis that the coefficient in column (1) of Table 1.7 (Panel b) equals the coefficient of the same regression that also includes $\Delta\omega_{it}$ as a control.

Economic magnitudes – To gauge an understanding of the magnitude of the effect on credit availability on gaps, we instrument the change in firm-level credit supply ($g(Credit_{it})$) with our predicted lending shifter. Before commenting on the estimation results of the 2SLS model, we must emphasize the limitations of this approach. First, the exclusion restriction is problematic, because the estimated effect of an expansion/contraction of credit supply also encompasses the effect of other outcomes that impact τ_{it}^{K}.[77] Second, the IV is going to give us a "local average treatment effect (LATE, [136]), that is, the effect of an additional unit of credit on the MRP-cost gaps firms for which credit actually changed (the "compliers").[78] With these caveats in mind, we present the estimates of the 2SLS model in Table 1.7, panel b. The economic magnitude of changes in credit availability on MRP-cost gaps appears to be substantial. On average, comparing two observationally similar firms whose change in credit supply is one standard deviation apart, we find the gap of the firm experiencing the larger credit expansion is reduced by 2.9 percentage points more with respect to the gap of the other firm (column (1)), and by 1.7 percentage points if we control for firm fixed effects (column (2)). Importantly, a supply-driven credit expansion worth one standard deviation of $g(Credit_{it})$ leads to a reduction of 3.6 percentage points in the τ^{K} of those firms that, before experiencing the shock, appear to be over-capitalized (column (3)). By contrast, an expansion of credit supply widens the distance between the marginal revenue product of capital and the user cost of those overcapitalized firms. The magnitude of this effect, however, is nine times smaller than the one estimated for undercapitalized

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77. Shifts in credit supply affect both the quantity of credit as well as other terms of the credit contract, such as interest rates, maturity, covenants – all of which can independently affect the availability of credit supply and the MRP-cost gap. Importantly, although these concerns implicate the consistency of the second stage coefficients, they do not invalidate the reduced form estimates reported in the rest of this section.

78. For example, a contraction in credit supply ($g(Credit_{it}) < 0$) is going to affect those borrowers whose loans are maturing during the year. Loans maturing in subsequent years are likely not responding to negative credit supply shifts in period t, unless failure or delays in debt repayments or covenant violations allow lenders to renegotiate the term of those contracts ([137]).

producers. Columns (4) and (5) confirms the shadow cost of capital of more productive firms drops more pronouncedly compared to the one of the less productive firms when hit by an equally large credit-supply shock, and that this effect is entirely driven by those producers that appear to be credit constrained.[79] For example, consider two undercapitalized firms ($\tau_{it-1} > 0$), located at the 75th and 25th percentiles of the TFPR distribution in $t-1$. All else being equal, a one-standard-deviation increase in firm-level credit supply reduces the gap of the latter by 1.9 percentage points more (-4.4 vs -2.5). Comparing the most productive of the two firms to another producer with average productivity and $\tau_{it-1} \leq 0$, the differential effect of a one-standard-deviation increase in credit supply is a larger reduction in $\Delta\tau^K_{it}$ of 3.7 percentage points for the former firm (-4.4 vs -0.7).

Quasi-experimental evidence from the European sovereign crisis – In Appendix A.10, we provide an additional piece of evidence that suggests part of the observed dispersion of τ^K_{it} can be explained by binding credit constraints that generate heterogeneous shadow costs of capital across firms. Building on the work of [48] (BLM henceforth), we study the relation between firms' exposure to the recent European Sovereign crisis and the gap τ^K.[80] Following BLM, we construct a measure of banks' exposure to the sovereign crisis, exploiting variation in firms' exposure to banks with differential holdings of government bonds issued by distressed sovereigns, and construct a firm-level credit-supply shifter as

$$\text{Sovereign Shock}_{iPRE} = \sum s_{iPRE}\text{Sovereigns}_{bPRE}\,,$$

79. As in columns (7) and (8) of Panel a, we normalize the variable ω_{it-1} to have zero mean and interact it with the credit shifter and with the dummy variable that flags firms with positive gaps in period $t-1$ (UNDERCAPITALIZED$_{it-1}$).

80. BLM shows the sovereign default and subsequent bailout of Greece in spring 2010 led banks more exposed to sovereign securities issued by Southern European countries (including Italian bonds) to sharply reduce their credit supply in response to a reassessment of the riskiness to their portfolios.

where $s_{iPRE} = \frac{\text{Credit}_{ibPRE}}{\sum_b \text{Credit}_{ibPRE}}$ is the share of bank b on firm i total credit, measured before the Greek bailout; Sovereigns$_{iPRE}$ is the exposure of bank b to Italian government bonds at the end of 2010:Q1 scaled by risk-weighted assets, which is a bank-specific measure of financial institutions' exposure to the sovereign shock. We find a strong, negative correlation between the variable Sovereign Shock$_{iPRE}$ and the estimated credit-supply shifter between 2009 and 2010 (Credit Shifter$_{i2010}$). The raw correlation is 16%. In terms of magnitude, we find a 9% reduction of Credit Shifter$_{i2010}$ (0.6 of a standard-deviation) associated to a one-standard-deviation increase in the variable Sovereigns$_{iPRE}$. Both correlations are significant with a p-value below 1%, and provide direct evidence of the link between the credit-supply shifters constructed using the shift-share approach in model (1.8) and events that affect the credit provision of individual banks.

Using the sovereign shifter, we investigate how the contraction of credit by more exposed banks affected the MRP-costs gap of their borrowers. Comparing two similar firms that, at the onset of the sovereign crisis, are one standard deviation apart in terms of lenders' exposure to the distressed sovereigns, we observe an increase of 0.5 percentage points in τ^K the year following the burst of the crisis, and a cumulative effect of 1 percentage point over a four-year period. To the extent that the change in the gap captures a change in the shadow cost of capital of affected firms, it suggests the real effects of the sovereign crisis are long-lasting.

1.5.1.4 Access to credit

Up to now, we have restricted the analysis of investment policy distortions and credit market frictions to producers who actively engage in credit market transactions. The summary statistics reported in Table 1.2, however, shows that the gap between realized marginal revenue products of capital and user costs is, on average, three times as large for firms that do not engage in credit market transactions.[81] Interestingly, we also observe a significant difference between the MRP-cost gaps of firms that report outstanding loan obligations and the estimated MRP-cost gaps of firms that utilize only revokable credit lines. Credit lines are often the first type of credit granted by banks in order to test borrowers' creditworthiness. The high interest rates, relatively low amounts, and revokable nature, however, make this type of credit product an inappropriate and expensive source of financing for capital expenditures in fixed assets (see Appendix A.2.1).

Although suggestive, we should be careful ascribing the difference between borrowers and non-borrowers to financial frictions. Credit market participation naturally co-varies with other phenomena affecting firm policies over their life cycle, and borrowers differ from non-borrowers in terms of age, size, and industry affiliation. Young and small firms may voluntarily restrain themselves from undertaking (partially) irreversible investments even if debt financing is available, especially when they operate in industries characterized by high demand uncertainty ([23]; [138]; [7]). We turn to regression analysis to try to disentangle the impact of credit market participation from these confounding effects. We run the following non-parametric difference-in-differences regression and analyze, within firm, the evolution of τ^K around the year in which firms enter the credit market:

$$y_{it} = \sum_{j=-3}^{7} \beta_j \mathbf{1}\{(t-t_0)=j\}_{it} + \Gamma X_{it} + \iota_t + \iota_i + \varepsilon_{it}\,, \tag{1.9}$$

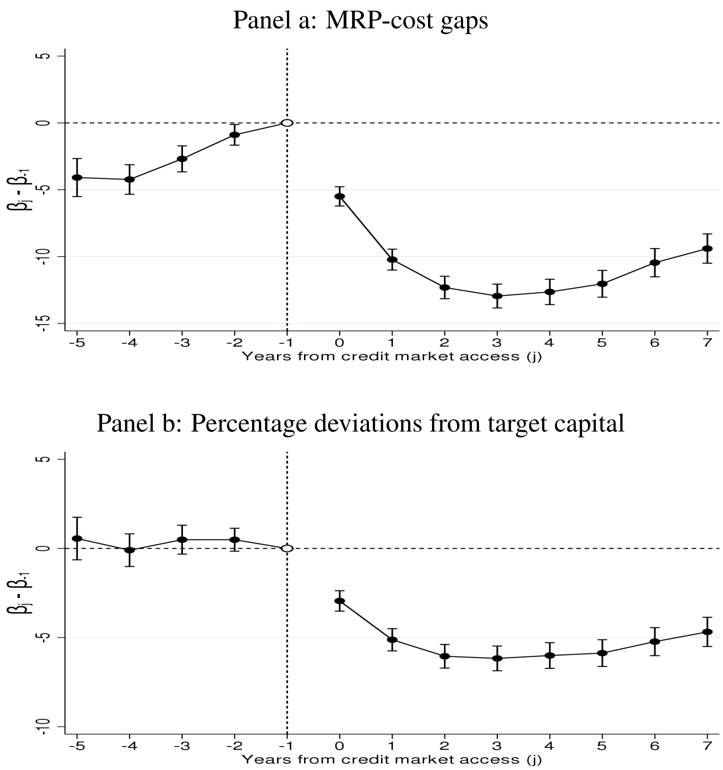
where t_0 represents the year of the change in status: $\text{BORROWER}_{it_0-1}=0$ (no outstanding bank debt) and $\text{BORROWER}_{it_0}=1$ (positive outstanding bank debt). We control for time trends with year fixed effects (ι_t); firm fixed effects (ι_i) allow us to exploit only

81. We do not observe the borrowing costs for firms that do not engage in credit market transactions. We follow the procedure described in section 1.4.1 and Appendix A.2.2 to construct an estimate of the interest rate they might have charged had they been able/willing to borrow.

within-firm variation. The vector of time-varying controls X_{it} includes a second-order polynomial in age, the natural logarithm of lagged assets, and lagged credit score. We allow the error term ε_{it} to display serial correlation at firm level. Figure 1.6 (Panel a) displays the estimates of the coefficients. $\hat{\beta}_j$ captures the average change in τ_{it}^K from year $j = -1$ (the baseline category in Model (1.9)) to year $j \neq -1$.

Figure 1.6. Access to credit markets

This figure displays the dynamic of MRP-cost gaps for capital (τ_{it}^K) (panel a) and percentage deviations from the target capital endowment ($(K_{it}^* - K_{it})/K_{it}$) (panel b) before-to-after transition of a firm into the credit market. The regression model is described by equation (1.9). All quantities on the y-axis are expressed in percentage points.



Comparing the level of the gap the year before credit market entry to the level of the year of entry and to one observed the following year, we estimate an average drop of 5 and 10 percentage points in τ^K, respectively. These stylized facts are revealing. They highlight that credit market participation (extensive margin) matters as much as, or even more than, the intensity of credit market interactions ([139]; [140]). Despite its importance, the extensive margin has received limited attention in the empirical literature, typically because of the lack of micro-level records that allow researchers to follow firms in their transition into credit markets.

Robustness – A concern with the comparison of borrowers and non-borrowers is related to an incorrect estimation of the missing prices. We worry that the larger gaps observed for non-borrowers might be driven by a systematic underestimate of their user cost of capital. A simple back-of-the envelop exercise suggests that imprecise estimates of r are unlikely to explain the large differences between borrowers and non-borrowers, as the interest rate of non-borrowers should be 22 *percentage points* higher than our estimate in order to equalize their average gap to the average gap of borrowers. In Appendix A.2.2, we provide other formal tests that suggest that an incorrect assessment of the potential borrowing rate that non-borrowers face is unlikely to be the driver of the estimates of model (1.9). First, we look at "crossover firms." That is, we identify those firms that are borrowers in year t but were not borrowers in $t-1$. For these observations, the difference between the observed interest rate in period t and the imputed interest rate in $t-1$ is only 28 basis points on average (median 0.18). We also perform an out-of-sample test, excluding a random sample of 10% of the firms for which we observe the interest rates, and implement our imputation procedure using the remaining 90% of the observations. For the subsample of excluded observations, the difference between the imputed and observed rate is, on average, economically negligible (-0.1 percentage points) and not significantly different from zero. Thus, consistent with previous evidence on the rigidity of interest rates, the change in τ^K as firms transition into the credit market is by and large driven by a drop in the MRP^K that signals firms use bank credit to harvest profitable investment opportunities.

Another concern with the previous calculations is related to discounting. The macro-finance literature has long recognized the presence of heterogeneous and state-contingent discount factors ([141]). We abstracted from this issue assuming shareholders are risk-neutral, and they discount cash flows at a constant rate ρ. This suggests that significant differences in the level of risk-aversion across entrepreneurs, and differences in the prices of risk of the same entrepreneur over time, could explain the larger gaps of non-borrowers. A proper account of the heterogeneous and stochastic nature of firms' discount factors is beyond the scope of the paper. However, in the spirit of the previous calculations, we calculate that non-borrowers shall have a discount factor twice as large as borrowers, in order to equalize the gap between these two group of firms. That is, if one dollar tomorrow is worth 95 cents today for borrowers (i.e., $\rho^{Borrower} = 0.95$, as we assume in the paper), the same dollar should be worth 45 cents to non-borrowers in order to equalize the average gap between these two groups. This level of a one-period discount factor for firms is a particularly high, especially because we are already "discounting" the realized MRP-cost gap of non-borrowers more than the one of borrowers through a lower estimated probability of exit ($P\{Exit_{it+1}\}$ (see equation (1.3a)).[82]

1.5.1.5 Extension to the Full Sample of Borrowers and Alternative Interest Rates

Full sample of borrowers – Analyzing the relation between credit market frictions and credit-supply shocks, we restricted our attention to the subsample of borrowers for which we observe the information on the APR on term loans. In Appendix A.10, we replicate all the analysis on the sample of borrowers for which we have information on the identity of the lender. As discussed in Section 1.4, this subsample include firms that only borrow

82. Our estimates suggest an expected probability of exit of 14% for non-borrowers and of 9% for borrowers.

drawing from credit lines, firms whose lenders are not in the TAXIA sample. Results are confirmed in both economic magnitude and statistical significance.

Alternative interest rates – Throughout the paper, we have used the APR on bank loans as a measure of borrowing costs. We have argued and shown empirically that investments in fixed assets display higher sensitivity to loans than to other types of credit products. How would the results of our analysis change if the APR on credit lines is used to construct τ^K? Appendix A.12.4 shows the MRP-cost gaps τ^K_{it} and the percentage deviations $(K^*_{it} - K_{it})/K_{it}$ are lower if we use the APR on credit lines, reflecting the higher level of $r^{CredLines}$ with respect to r^{Loans}.[83] However, all the statistical relationships discussed in this section are found to be highly robust to changes in the reference interest rate.

1.5.2 Labor Market Distortions

We now move to the analysis of labor policies and labor market frictions. We focus, in particular, on the firing restrictions imposed by Article 18 of the Italian Workers' Statute. As discussed in section 1.2, contractual frictions prevent wage adjustments from undoing the government-mandated severance payment imposed on firms larger than 15 employees. In this situation, we expect the size-dependent provisions of Article 18 to have an effect on employment policies and on the allocation of labor across producers.

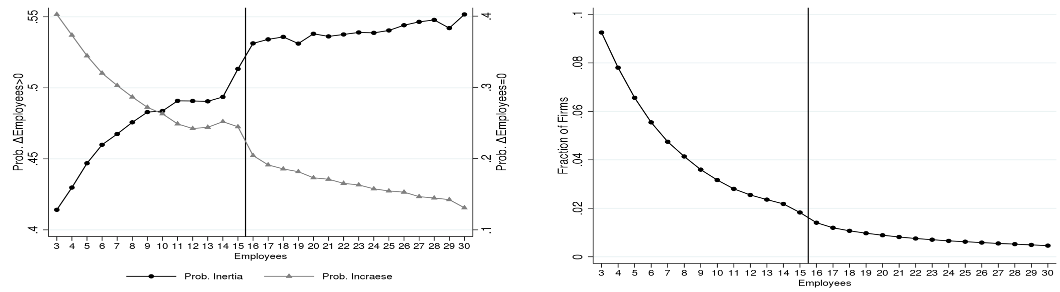
We begin our analysis showing the impact of the employment protection provision on firms' propensity to grow and on the size distribution of firms around the 15-employees threshold. Figure 1.7 Panel a (left), displays the probability of increasing the labor force ($\text{EMPLOYEES}_{it} > \text{EMPLOYEES}_{it-1}$, left axis) and the probability of labor-force inertia ($\text{EMPLOYEES}_{it} = \text{EMPLOYEES}_{it-1}$, right axes) as a function the number of employees of the firm.

83. On average, the nominal APR on credit lines is 12.5%.

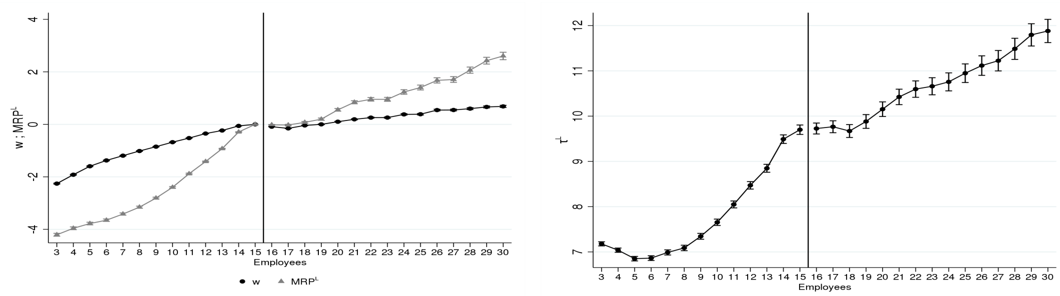
Figure 1.7. Labor market frictions

This figure studies the impact of size-dependent government-mandated severance payments on firms' employment policies. Panel a reports the probability of employment inertia and probability of upward adjustment across firms of different size (left) and the size distribution (right) as a function of firm size. The probability of inertia is the probability that $\text{EMPLOYEES}_{it} = \text{EMPLOYEES}_{it-1}$; the probability of upward adjustment is $\text{EMPLOYEES}_{it} > \text{EMPLOYEES}_{it-1}$. Panel b displays the average marginal revenue product of labor (MRP^L_{it}) and wages (w_{it}) (left) and the average MRP-cost gap of labor τ^L_{it} (right) as a function of firm size. Panel c displays the average percentage deviation from target employment $(L^*_{it} - L_{it})/L_{it}$ as a function of firm size. marginal revenue products, wages, and MRP-cost gaps are expressed in thousands of Euros.

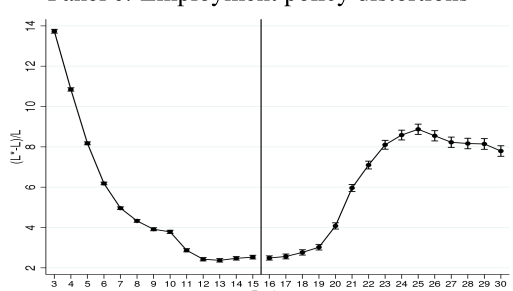
Panel a: Inertia and adjustment probability (left) and size distribution (right)



Panel b: MRP^{L}and wages (left) and MRP-cost gaps (right)



Panel c: Employment policy distortions



The probability of workforce inertia jumps by 0.5 percentage points at the threshold.[84] This finding suggests the provisions of Article 18 generate a significant rigidity in the labor

84. These results are in line with previous empirical studies that analyzed the impact of Article 18 on firms employment policies ([142], [21]).

market. Because adjustment has an option value, firing costs also affect hiring decisions ([62]): in anticipation of a possible reversal of consumer demand, firms will hire less than they would have in a frictionless environment, in order to avoid incurring high firing costs when downscaling is needed. Consistent with this theoretical prediction, we find a sharp drop in the probability of hiring new workers right-after the 15-employees threshold, inverting an upward tendency observed to the left of the threshold. Figure 1.7 panel a (right) shows that Article 18 has implications for the size distribution. The fraction of firms by number of employees generally decays with size following a power law, but the rate of decay changes markedly past the 15-employees threshold ([58]).

Price versus quantity adjustments – In the absence of wage rigidities, theory predicts that government-mandated severance payment would be neutralized by appropriately designed wage contracts. Firing costs would be transferred to workers in the form of reduced wages, with no effects on firms' employment policies ([22]). This is not what we find in the data.

Figure 1.7, Panel b (left), plots average yearly wages and average Marginal Revenues Products of labor by size class. To account for time, industry, and local labor trends, we use firm-level deviations from the year-industry-province mean; then we aggregate the data, taking the average of firm wages within each size cell. We normalize both series to zero at size 15, to make the patterns more easily comparable. Wages increase smoothly with firm size; however, we do not find a noticeable reduction in the wage rate at or after the 15 employees threshold. By contrast, the figure highlights a significant response of the marginal revenue product around the threshold, suggesting that - due to the rigidity of wages - the labor market regulation affects firms' labor demand.

The rigidity of wages is consistent with the institutional features of the Italian labor market. Evidence of wage rigidity can be gathered from nationally representative firm-level surveys. According to the 2010 Bank of Italy survey on industrial and service firms, only 20% of firms engage in some form of firm-employees wage negotiations. On average, the nationally negotiated minimum wage contracts account for 80% of the total wage, whereas the residual 20% is set at the firm level ([143]). [65] reports similar estimates for the 1990s. Firm-level wage bargaining, in the sporadic instances when it takes place, is limited to upward adjustments, because nationally-set minimum wages are legally binding ([144]). Data from the 2010 Structure of Earning Survey administered by the National Statistical Institute show the firm-level component of workers' compensation is mostly composed of *una tantum* bonuses, rather than adjustments in the hourly or daily wage rate.

Our data corroborate these findings. We run a linear regression that includes a set of year-by-province-by-industry dummies, and dummies for age and size deciles. This simple model explains 50.3% of the dispersion in average annual wages.[85] Firm-level (log) TFPR and ROA - two measures of productivity and profitability - are able to explain only an additional 1% of the variance in wages.

Because wages are rigid, labor demand is expected to react. Indeed, Figure 1.7 panel b (left) highlights a significant response of the marginal revenue product around the threshold, suggesting that - due to the rigidity of wages - the labor market regulation affects firms labor demand.

Static effects – Figure 1.7, Panel b (right), studies the impact of the size-dependent EPL on the distribution of the labor gap τ^L. The average labor gap increases as we approach the regulatory threshold, possibly reflecting forgone growth opportunities in order to avoid the cost being subject to the labor irreversibility. Mirroring the distribution of MRP^L, we find a significant kink right at the threshold: gaps become flat immediately past the threshold,

85. In a similar institutional context, [145] shows that a large share of the observed wage dispersion across Spanish manufacturing firms is explained by geographic and temporal differences in labor markets.

as labor adjustment takes place. Above 20 employees, gaps start growing again, albeit at a slower pace.

Dynamic effects – Next, we study the dynamic effects of the provisions of Article 18 on the static distribution of gaps. We study how firms of different size respond to realized changes in TFPR productivity ($\Delta\omega$).[86] More formally, for all firms below 30 employees, we estimate the model:

$$y_{it} = \sum_{j=1}^{30} \beta_j D(j)_{it} + \gamma \Delta\omega_{i,t} + \sum_{j=1}^{30} \delta_j D(j)_{it} \Delta\omega_{i,t} + X_{it}\theta + \varepsilon_{it}\,, \tag{1.10}$$

where y_{it} is τ^L_{it}, MRP^L_{it}, w_{it}, and $(L^*_{it} - L_{it})/L_{it}$, alternatively. The variable $\Delta\omega_{i,t}$ is the change in TFPR between year $t-1$ and t. $D(j)_{it}$ are a set of dummies equal to the value of 1 if EMPLOYEES_{it-1} equals j. The vector of controls includes lagged TFPR, a quadratic in lagged age, and (alternatively) industry-by-year-by-province fixed effects or year and firm fixed effects. The vector δ_k provides an estimate of the association between changes in productivity and the dependent variables for different size categories. We are interested, in particular, in firms around the 15-employees threshold. To ease the discussion, here we focus on the comparison of δ_{15} with δ_{14} and δ_{16}, that is, firms at the threshold vis-a-vis those below and immediately above it.[87] Results are provided in Table 1.8. The first column of Panel a shows that changes in TFP for firms at the threshold induce larger gaps for firms right below the threshold relative to smaller or larger firms. In column 2, we focus on the effect of positive innovations in TFPR ($\Delta\omega^+_{it}$), restricting the estimation sample to firm-year observations for which we observe a $\Delta\omega_{it} > 0$. The lower response of firms at the

86. See [61] for a detailed analysis of the dynamic implications of size-dependent labor market regulation using structural methods.

87. In Appendix A.11, we provide the entire distribution of the estimates δ_j, showing that results are not affected by narrowing our discussion to these three categories.

Table 1.8: Labor market regulations and response to TFP shocks

This table investigates the response of labor gaps (τ_{it}^{L}) and marginal revenue product of labor (MRP_{it}^{L}), wages (w_{it}), and percentage deviations from target labor ($\frac{L_{it}-L_{it}^{*}}{L_{it}}$) to changes in firm-level productivity (TFPR, ω_{it}). The regression model is specified in equation (1.10). The vector of controls includes lagged TFPR, a quadratic in age, and (alternatively) industry by year by province fixed effects or year and firm fixed effects. Standard errors (in parenthesis) are clustered at the firm level.

	(1)	(2)	(3)	(4)
	CHANGES IN ω	POSITIVE CHANGES IN ω	CHANGES IN ω	POSITIVE CHANGES IN ω
Panel a: Dep. Var. τ_t^L				
$\delta_{15}-\delta_{14}$	1.468	5.013	.607	5.346
	(1.326)	(2.226)**	(.992)	(2.226)**
$\delta_{15}-\delta_{16}$	1.222	5.156	1.13	4.634
	(1.367)	(2.633)*	(1.337)	(2.285)**
Panel b: Dep. Var. MRP_t^L				
$\delta_{15}-\delta_{14}$	1.774	5.022	.738	5.28
	(1.865)	(2.659)*	(1.031)	(2.275)**
$\delta_{15}-\delta_{16}$	1.606	5.419	1.403	4.96
	(1.634)	(2.744)**	(1.445)	(2.404)**
Panel c: Dep. Var. w_t				
$\delta_{15}-\delta_{14}$	-.163	-.403	-.13	-.472
	(.509)	(1.204)	(.277)	(.396)
$\delta_{15}-\delta_{16}$	-.145	.047	.011	.167
	(.682)	(1.146)	(.241)	(.408)
Panel d: Dep. Var. $(L_t^*-L_t)/L_t$				
$\delta_{15}-\delta_{14}$	.285	5.141	-.448	3.191
	(1.327)	(1.931)**	(1.121)	(2.177)**
$\delta_{15}-\delta_{16}$	1.13	1.589	1.137	.715
	(1.271)	(3.92)	(1.051)	(2.168)
FIRM CONTROLS	Y	Y	Y	Y
INDUSRY X YEAR X PROVINCE FE	Y	Y	N	N
YEAR	N	N	Y	Y
FIRM	N	N	Y	Y
OBS	1,759,883	727,419	1,794,323	724,687

threshold relative to firms before the threshold become larger in magnitude and statistically significant. Columns 3 and 4 confirm that results hold true also when controlling for firm time-invariant, unobserved heterogeneity using firm fixed effects. This result is consistent with the hypothesis that firms with 15 employees do not increase their size in response to a positive TFPR shocks in order to avoid becoming subject to Article 18 provisions. Panels b and c of the table provide additional evidence in favor of this conjecture: they show that the difference in MRP-cost gaps is entirely driven by labor-quantity adjustments (change in MRP^L), with no significant differences in wages. Finally, Panel d shows the effect of TFPR shocks on employment policy distortions ($(L^*_{it} - L_{it})/L_{it}$). A one-percentage-point positive increase in TFPR is found to increase under-employment by 5 percentage points for firms of size 15, relative to those of size 14.

1.5.3 Robustness checks

Average versus marginal wages – One might worry that average annual wages are poor proxies of the marginal ones. To gauge an understanding on the impact of an imperfect measurement of the user cost of labor, we use wages of newly hired workers as an alternative proxy of the user cost of labor (see section 1.4.1). We find that wages of new workers are higher than the wages paid to previously employed workers (on average, 15% higher), an effect likely due to a combination of nominal rigidities in the inter-temporal adjustment of wages of infra-marginal workers, and to the different skill composition of newly hired employees. This difference, however, has a limited impact on MRPL-wage gaps and percentage deviations. In Appendix A.12.4, we show that, consistent with rigid wages and labor-quantity adjustments, the level of τ^L and $(L^*_{it} - L_{it})/L_{it}$ is lower, but using wages of new hires as a proxy of w_{it} does not affect our findings with respect to the static and dynamic implications of the size-dependent EPL.

Informal labor and misreporting – Considering the incidence of the informal labor on the Italian economy, one might argue that these patterns could be explained by firms misreporting their labor force, in order to avoid being subject to the provisions of Article 18. Anecdotal evidence suggests the problem of hidden labor is more severe in the informal sector of the economy. All firms in our sample, instead, are incorporated entities, which are subject to a closer scrutiny by government officials and unions. In Appendix A.9, we provide two pieces of evidence suggesting that the patterns in Figure 1.7 reflect true distortions rather than misreporting. First, we show that even in highly unionized industries (e.g., manufacturing), we find patterns very similar to industries with low unionization levels (e.g., services). Second, if capital and labor are partially substitutable in production, theory suggests that firms should respond to an increase in the cost of labor demanding more capital. Consistent with a stronger substitution effect due to changes in the relative cost of inputs, the capital gap τ^K spikes down to the left of the threshold and then up to the right. A similar pattern is observed for the distribution of $(K_{it} - K_{it}^{*})/K_{it}$.[88] The ability to effectively substitute labor services for capital services is a function of the relative intensity of these two inputs in production. Thus, we expect employment policy distortions to be higher in labor-intensive industries than in capital-intensive ones. Using the industry ratio of θ^L/θ^K as a measure of labor intensity (relative to capital) of the production technology, we find that τ^L responds more strongly to the provisions of Article 18 in more labor-intensive industries.

Overtime hours – Another concern is related to the possibility that firms might respond to the size-dependent EPL by adjusting the number of hours they ask their employees to work, or by incentivizing overtime. The data in our possess do not contain information on

88. [146] provide similar evidence of capital deepening in response to variation in EPL in the United States. [147] study the capital-labor substitution when EPL interact with financial frictions. [148] study the impact of Article 18 on capital accumulation within a general equilibrium framework.

these variables. However, the Italian institutional framework and previous empirical studies leave us confident that these factors are not a major force driving our results. First, firms are limited in their ability to increase hours, because the Italian labor law allows a maximum 40 hours per week and 8 hours per day. Moreover, [143] shows that overtime pay accounted for a relatively low portion (around 4%) of monthly earnings in the industrial sector. They also find that overtime hours (as a fraction of total hours) are uncorrelated with the degree of wage rigidity at the firm level.

1.6 Firm-level Counterfactuals and Policy Distortions

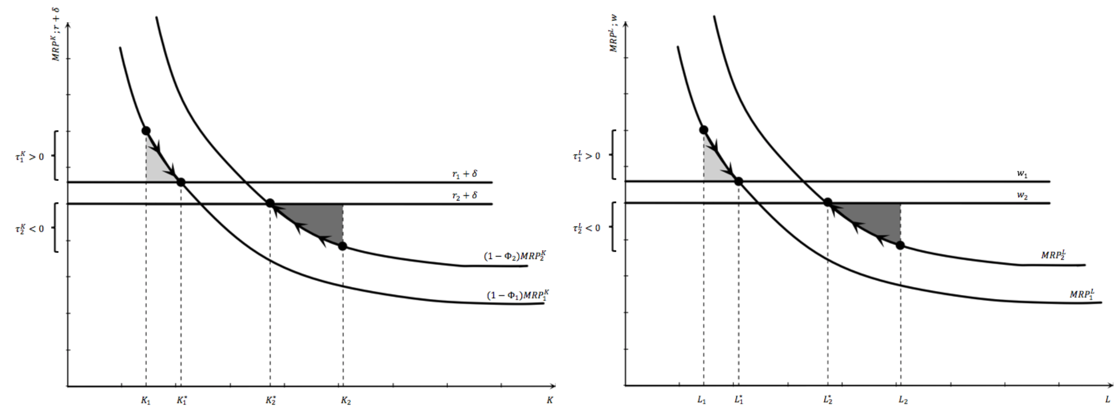
Do the estimated MRP-cost gaps imply economically relevant investment and employment distortions? How much labor and capital do firms need to acquire/dismiss in order to close them? To answer these questions, we define the following counterfactual input demands:

$$\begin{aligned} K_{it}^* &:= MRP^K(K_{it}^*) = r_{t+1} + \delta \\ L_{it}^* &:= MRP^L(L_{it}^*) = w_{it} \,. \end{aligned} \tag{1.11}$$

We refer to these counterfactual quantities as *target labor force* and *target capital endowment* (L_{it}^* and K_{it}^*). Figure 1.8 provides a graphical representation of the relation between gaps and target endowments.

Figure 1.8. MRP-cost gaps and firm policies

This figure provides a graphical representation of gaps (τ_{it}^K and τ_{it}^L) and their relation to target input demands (K_{it}^* and L_{it}^*).



Under the assumptions that the user costs each firm faces do not change for moderate adjustments of its input demand, we calculate the *deviations from targets* as

$$\frac{L_{it}^* - L_{it}}{L_{it}} = -\tau_{it}^L \cdot \left(\frac{\partial MRP^L}{\partial L}\bigg|_{L \approxeq L_{it}\,;MRP^L \approxeq MRP_{it}^L} \right)^{-1} \tag{1.12a}$$

$$\frac{K_{it}^* - K_{it}}{K_{it}} = -\frac{\tau_{it-1}^K}{\rho} \cdot \left(\frac{\partial MRP^K}{\partial K}\bigg|_{K \approxeq K_{it}\,;MRP^K \approxeq MRP_{it}^K} \right)^{-1}, \tag{1.12b}$$

where the terms in parentheses are the inverse of the slope of marginal revenue product schedules evaluated in a neighborhood of the observed input demands and realized *MRP*s. $(L_{it}^* - L_{it})/L_{it}$ and $(K_{it}^* - K_{it})/K_{it}$ have an intuitive interpretation. They help us read MRP-cost gaps in terms of how many extra workers a firm should hire (or fire), and how much capital expenditures should change, in order to close the gap between realized marginal revenue products and observed user costs.

Being able to construct firm-level counterfactual input demands is important for two reasons. First, evaluating the extent of misallocation necessarily requires computing counterfactual levels of output. As we discuss in the next section, L^* and K^* are key ingredients in our attempt to do so. Second, thinking about policy distortions in terms of percentage deviations is also important if one wants to compare the magnitude of the capital and labor adjustments needed to close firm-specific gaps. To clarify this point, consider a case where $\tau^K_{1t} > \tau^K_{2t} > 0$. Based on the ordinality of MRP-cost gaps, one might be tempted to conclude firm 1 investment policies are more distorted than firm 2 policies, because the distance between firm 1 capital stock from its optimal endowment is larger than the distance of firm 2. This logic has a caveat. What matters is not only the size of the gap but also the rate at which one additional unit of capital closes the gap. For example, consider small- and large-size firms with a similar $\tau^K > 0$. Despite the similar gaps, the implied investment policy distortion is expected to be larger for the latter because, as the data suggest, the slope of the MRP^K schedule in the $K - MRP^K$ plane is much steeper for small firms than for large firms. Similar considerations apply to labor gaps.[89]

We estimate slopes of marginal revenue products via local linear regressions. For each input and each macro-industry (1-digit code), we sort observations into 100 cells defined by deciles of the distribution of L and MRP^L (K and MRP^K). Within each cell, we run a linear model in first difference: $\Delta L_{it} = \beta^L \Delta MRP^L_{it}$ and $\Delta K_{it} = \beta^L \Delta MRP^K_{it}$.[90] Regressions are run separately for each macro-industry (1-digit code) to account for heterogeneous adjustments due to different technologies of production. Table A.15 in Appendix A.7 reports the summary statistics of the distribution of the estimated slopes. On average, a change in capital of 1,000 Euros reduces the marginal revenue product of capital by 0.13%. A

89. The estimated slopes confirm this intuition. Small firms tend to have higher Marginal Products, but significantly steeper MRP slopes than larger firms: large (small) MRP-cost gaps might translate to relatively small (large) distortions depending on the slope of the MRP-cost schedule.

90. First differencing allows us to exploit only within-firm variation, and smooth out the impact of outliers. We also experimented with other specifications in levels with fixed effects. This specification produces estimates of $\hat{\beta}$s in the same ballpark of the first-difference estimator, with some more extreme values.

positive 1-unit-change of effective labor reduces the marginal revenue product of labor by 8,000 Euros.

Table 1.2, Panel d, reports the summary statistics of deviations from targets $(L^*_{it}-L_{it})/L_{it}$, $(K^*_{it}-K_{it})/K_{it}$. We multiply them by 100 to express them as percentages. Figure 1.2 (Panel b) provides a graphical representation of their distribution. On average, to close their gaps, firms should increase capital expenditure by an amount worth 16% of their assets in place, and they should expand their (effective) labor force by 11% more. Mirroring the distribution of MRP-cost gaps, these numbers are driven by the right-tail of the distributions. In fact, central percentiles are occupied by firms whose capital and labor endowment appears to be relatively undistorted, according to our metric. To close the gaps of the median firm, it would be sufficient to invest an amount of capital worth 1% of firm assets and hire 3% more units of effective labor.

Importantly, we observe both positive and negative deviations at the tails or the distributions of $(L^*_{it}-L_{it})/L_{it}$ and $(K^*_{it}-K_{it})/K_{it}$. Based on our estimates, 25% of the firms-year observations should have invested to acquire 6% more physical capital and expand their labor force 15% more. On the contrary, another 25% of firms should sell 1% or more or their fixed assets and over 10% of observations should reduce their quality-adjusted labor demand by 1% or more.

1.6.1 Investment Policy Distortions

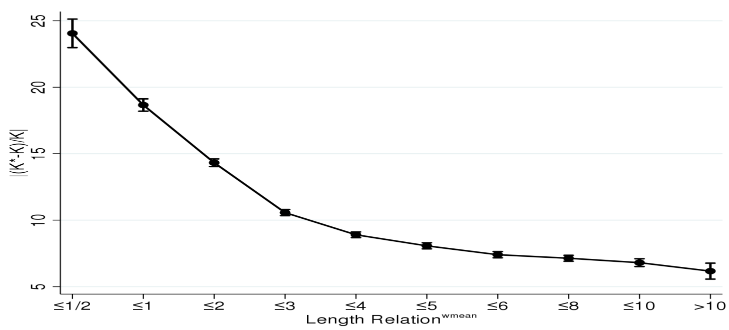
To gauge an understanding of the relation between credit market frictions and policy distortions, we replicate the analysis of Section 1.5.1 using the percentage deviations from target capital $(K^*_{it}-K_{it})/K_{it}$ as an outcome variable.

Information frictions and relationship lending – Figure 1.9 shows the amount of investment needed to close the gap is worth 25% of installed capital for firms with newly established relations, but it reduces to 10% after three years, and to 6 % after 10 years of continuous bank-firm interactions. We use regression analysis to disentangle the effect of relationship lending from other correlated variables.

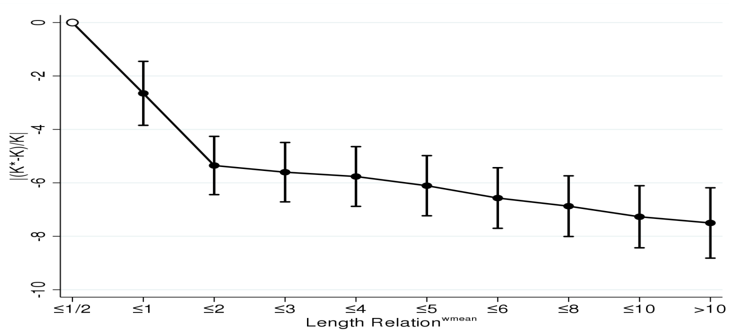
Figure 1.9. Percentage deviations from target capital and length of lending relations

This figure displays the relation between percentage deviations from target capital ($(K^*_{it}-K_{it})/K_{it}$) and the length of lending relationships (LENGTH RELATION$^{wmean}_{it}$). Panel a displays the raw correlation. Panels b, c, and d plot the regression coefficients associated with dummy variables indicating a different length of lending relationships (omitted category: LENGTH RELATION$^{wmean}_{it}\leq$0.5 years). The regression model includes firm-level controls and industry by province by year fixed effects. In panel c, undercapitalized firms are those with $\tau^K_{it-1} > 0$. In panel d, high-TFPR firms are those with TFPR above the median of the distribution of TFPR (ω_{it}). All quantities on the y-axis are expressed in percentages. The length of relationships is expressed in years.

Panel a: Raw Correlation



Panel b: With controls



Panel c: With controls - Under- vs overcapitalized firms

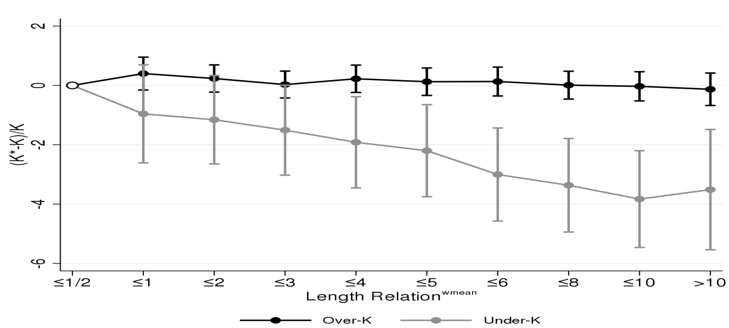
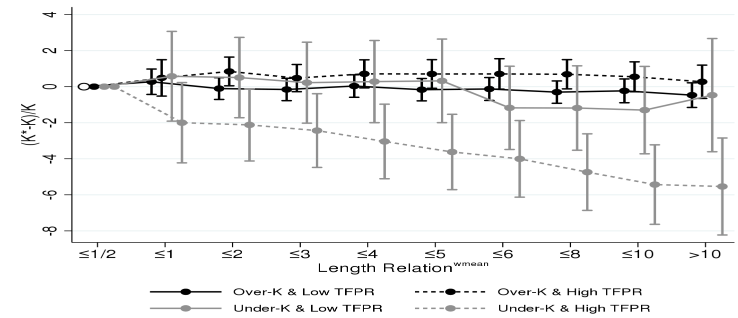


Figure 1.9 (cont'ed): Percentage deviations from target capital and length of lending relations

Panel d: With controls - Productivity



The empirical specifications mirror the ones adopted to test the MRP-cost gap τ_{it}^{K} (equation 1.6), but using percentage deviations ($(K_{it}^{*}-K_{it})/K_{it}$) as the dependent variable. Results are presented in Table 1.9, Panel a (continuous variable), and Figure 1.9, Panels b–d (discrete variable). On average, one additional year of continuous interactions leads to a reduction in the investment gap of almost 0.5 percentage points for those firms that operate below scale. The costs of asymmetric information in credit markets are particularly high for highly productive firms, especially for those under scale.[91]

Figure 1.10 shows how the benefits of relationship lending vary across firms in different stages of their life cycle as a function of the strength of their credit market interactions.

91. The inclusion of firm fixed effects and control for simultaneous productivity does not affect the results.

Table 1.9: Percentage deviations from target capital and credit market frictions

This table investigates the relationship between percentage deviations from target capital ($\frac{K_{it}-K^*_{it}}{K_{it}}$) and proxies of credit market frictions (Panel a) and credit-supply shocks (Panel b). In Panel a, the main regressors are: the weighted average length of lending relationships (LENGTH RELATION$_{it}{}^{wmean}$) and the length of bankruptcy litigations in court (LENGTH BANKRUPTCY). The set of firm-level controls includes age and size dummies (deciles), credit score dummies (9 values), assets turnover, ROA, cash flows over assets, leverage, and the number of active credit relationships. These regressions include year by province by industry (2-digits industry codes) fixed effects. In Columns (2)—(4) regressions also include the interactions of all variables and fixed effects with UNDERCAPITALIZED$_{it-1}$(=1 if $\tau^K_{it-1} > 0$), TFPR$_{it}$ (mean-zero ω_{it}), and UNDERCAPITALIZED$_{it-1}$x TFPR$_{it}$. In Columns (5) and (6) we include the following set of province-level controls, measured in 2007: population, GDP, unemployment rate, active firms per resident, firm exit rate, Herfindahl-Hirschman Index of credit market concentration, and the number of active credit institutions. In Column (5) we include year by industry fixed effects.; in Columns (6) we include year by industry by macro-region (North, Center, South of Italy) fixed effects.
In Panel b, Column (1) reports the OLS coefficient; Columns (2)–(4) report the reduced form regressions, where we project the percentage deviation $\frac{K_{it}-K^*_{it}}{K_{it}}$ onto the credit shifter (CREDIT SHIFTER$_{it}$); Columns (5)–(7) report the Instrumental Variables (IV) regressions, where we instrument the percentage change in credit supply using the credit supply shifter. All regressions include 2-digit industry by year by province fixed effects and the following set of lagged controls: productivity (TFPR), the weighted average of the length of lending relationships, a second order polynomial in age, log assets, credit score dummies (9 values), assets turnover, ROA, cash flows over assets, leverage, and number of active credit relations. In Columns (3)–(4) and (6)–(7) regressions also include the interactions of all variables and fixed effects with UNDERCAPITALIZED$_{it-1}$, TFPR$_{it-1}$(mean-zero ω_{it-1}), and UNDERCAPITALIZED$_{it-1}$x TFPR$_{it-1}$. Regressions are run on the sub-sample of borrowers with outstanding loans for which we observe the APR on loans. Standard errors (in parenthesis) are clustered at the firm level.

Panel a: Asymmetric information and bankruptcy costs

	(1)	(2)	(3)	(4)	(5)	(6)
	$\lvert(K^*_t-K_t)/K_t\rvert$		$(K^*_t-K_t)/K_t$		$(K^*_t-K_t)/K_t$	
LENGTH RELATION$_{t-1}{}^{wmean}$	-0.317	-0.020	-0.775	-0.023	-0.171	-0.178
	(0.029)***	(0.014)**	(0.026)***	(0.014)	(0.026)***	(0.026)***
LENGTH RELATION$_{t-1}{}^{wmean}$		-0.284		-0.250		
x UNDERCAPITALIZED$_{t-1}$		(0.049)***		(0.049)***		
LENGTH RELATION$_{t-1}{}^{wmean}$			-0.355	0.049		
x TFPR$_t$			(0.064)***	(0.030)		
LENGTH RELATION$_{t-1}{}^{wmean}$				-0.781		
x UNDERCAPITALIZED$_{t-1}$x TFPR$_t$				(0.104)***		
LENGTH BANKRUPTCY					0.103	0.032
					(0.041)**	(0.042)**
FIRM CONTROLS	Y	Y	Y	Y	Y	Y
PROVINCE CONTROLS	N	N	N	N	Y	Y
AGE AND SIZE AND CRED. SCORE FE	Y	Y	Y	Y	Y	Y
INDUSTRY X YEAR X PROVINCE FE	Y	Y	Y	Y	N	N
INDUSTRY X PROVINCE FE	N	N	N	N	Y	N
INDUSTRY X YEAR X M. REGION FE	N	N	N	N	N	Y
ADJ. R2	0.025	0.032	0.032	0.032	0.030	0.030
OBS.	1887314	1633484	1633697	1633484	1822631	1822618

Table 1.9 (cont'ed): Percentage deviations from target capital and credit market friction

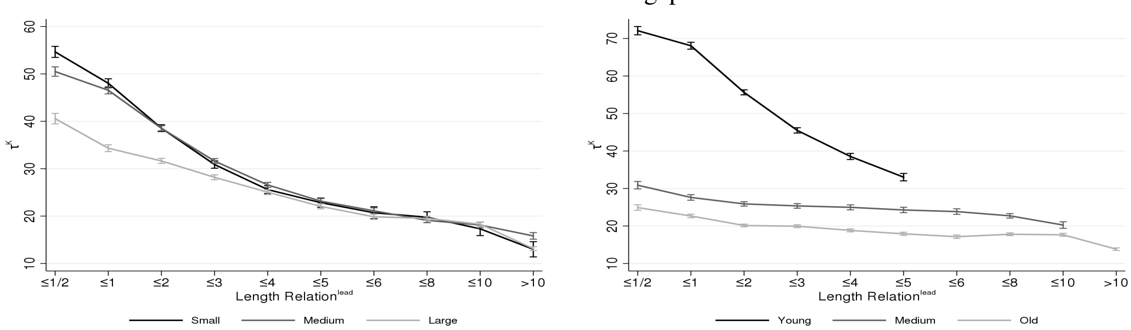
Panel b: Credit-supply shocks

Dep Var: $\Delta((K_t^* - K_t)/K_t)$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS		Reduced Form			IV	
g(CREDIT$_t$)	-0.566				-1.262	-0.426	-0.409
	(0.016)***				(0.188)***	(0.076)***	(0.084)***
CREDIT SHIFTER$_t$		-0.265	-0.086	-0.082			
		(0.039)***	(0.015)**	(0.016)***			
CREDIT SHIFTER$_t$			-0.168	-0.151			
x UNDERCAPITALIZED$_{t-1}$			(0.073)**	(0.072)**			
CREDIT SHIFTER$_t$				0.034			
x TFPR$_{t-1}$				(0.039)			
CREDIT SHIFTER$_t$				-0.299			
x UNDERCAPITALIZED$_{t-1}$x TFPR$_{t-1}$				(0.172)*			
g(CREDIT$_t$)						-0.779	-0.733
x UNDERCAPITALIZED$_{t-1}$						(0.345)**	(0.342)**
g(CREDIT$_t$)							0.145
x TFPR$_{t-1}$							(0.196)
g(CREDIT$_t$)							-1.594
x UNDERCAPITALIZED$_{t-1}$x TFPR$_{t-1}$							(0.781)*
FIRM CONTROLS	Y	Y	Y	Y	Y	Y	Y
INDUSTRY x YEAR x PROVINCE FE	Y	Y	Y	Y	Y	Y	Y
ADJ. R2	0.021	0.019	0.038	0.038			
OBS.	1611783	1611783	1596403	1596403	1611783	1596403	1596403

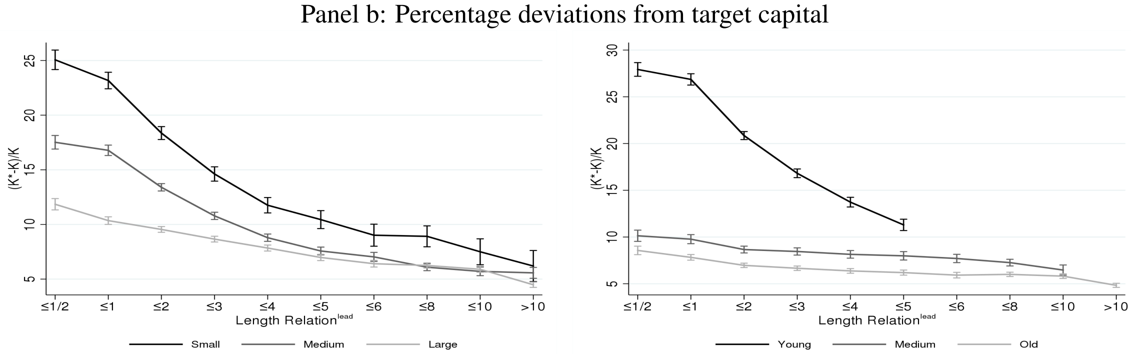
Figure 1.10. Age-size heterogeneity

This figure shows the average MRP-cost gap for capital (τ_{it}^K) (panel a), and average deviation from the target capital endowment ($(K_{it}^* - K_{it})/K_{it}$) (panel b) across the distribution of LENGTH RELATION$_{it}^{wmean}$ (x-axis) by age and size groups. All quantities on the y-axis are expressed in percentages. The length of relationships is expressed in years.

Panel a: MRP-cost gaps



Panel b: Percentage deviations from target capital



If scale economies exist in information production, and the monitoring cost per dollar falls with the size of the loan, the cost of asymmetric information falls with borrower size and transparency. Confirming a robust empirical finding in the literature, asymmetric information frictions appear to be particularly taxing for small and young firms ([67]; [45]; [48]).

Bankruptcy costs – The association between investment policy distortions of capital and bankruptcy costs is also confirmed. All else being equal, our estimates suggest that longer bankruptcy litigations depress investment, because the average percentage deviations from the target capital are higher in geographical areas where the judiciary system is more inefficient (Table 1.9, Panel a).

Credit availability – Table 1.9 (Panel b) studies how $(K^*_{it}-K_{it})/K_{it}$ responds to changes in the availability of credit. In line with the negative relation found for τ^K_{it}, the distance between capital and target capital decreases as more credit becomes available (reduced form regressions). Using the 2SLS regressions to quantify the relation between credit availability and gaps, we find that, everything else being equal, an increase of one standard deviation in credit (driven by an expansion of credit supply) is associated, on average, with a 0.45 percentage points drop in $(K^*_{it}-K_{it})/K_{it}$ (-1.20*0.37) for firms that were undercapitalized the period before they experienced the credit shock.[92] This effect is entirely driven by the most productive firms that operate below their optimal capital endowment. By contrast, overcapitalized firms seem to respond to an expansion of credit supply mostly rolling over their debt, rather than undertaking new investment.

Access to credit – Finally, we assess the impact of credit market participation on investment policies. We calculate that the amount of investment non-borrowers need to close their

92. As in Table 1.7, we normalize the variable ω_{it-1} to have zero mean in the estimation sample. The IV regressions in Table 1.9 (Panel b) are subject to the same caveats discussed above.

capital gaps is 3.5 times larger than the one borrowers need. We use the non-parametric, within-firm difference-in-differences model in equation (1.9) to study the transition into credit markets. We estimate a significantly higher deviation from optimal capital endowment before a firm enters into a credit market transaction (Figure 1.6, Panel b). Then, we estimate that, on average, $(K_{it}^{*} - K_{it})/K_{it}$ drops by 3 and 5 percentage points the year of entry and to one of the following year, respectively.[93]

1.6.2 *Employment Policy Distortions*

We conclude this section studying the local impact of the size-dependent employment protection law on percentage deviations from target labor $(L_{it}^{*} - L_{it})/L_{it}$.

Static effects – Figure 1.7, Panel c plots the average percentage deviations as a function of firm size, highlighting a structural change at around 15-employees. Whereas employment policy distortions monotonically decrease in size for firms with less than 15 employees, possibly reflecting the relaxation of other frictions as firms become older and bigger. After the 15-employees threshold, however, the relation between distortions and size becomes positive. This finding suggests the increase in labor adjustment costs due to the labor market regulation offsets the reduction of other components of the shadow cost of labor that decrease as firms become older and larger (e.g., reduced adjustment costs of production, less economic uncertainty, or a relaxation of financial frictions).

Dynamic effects – Next, we estimate the empirical model in equation (1.10) to study the response of $(L_{it}^{*} - L_{it})/L_{it}$ for firms to the left and to right of the regulatory threshold. Results are reported in Table 1.8, Panel d. Confirming the results of section 1.5.2, we find

93. Comparing Figure 1.6 Panel a to Panel b, we find a pre-entry upward trend in the MPR-cost gap τ^{K} that is not found in the dynamic of the percentage deviation $(K_{it}^{*} - K_{it})/K_{it}$. This trend is due to the fact that, for small and young producers, a large τ^{K} translates into a moderate increase in $(K_{it}^{*} - K_{it})/K_{it}$, because the slope of the MRP_{it}^{K} schedule is steeper for these firms.

that, in response to a positive TFPR shock, $(L^*_{it} - L_{it})/L_{it}$ increases more for firms below the threshold (14 employees) than for firms at the threshold (15 employees). A 1-percentage-point positive increase in TFPR is found to increase under-employment by 5 percentage points for firms of size 15, relative to those of size 14. This result, which is robust to the inclusion of firm fixed effects, suggest firms with 15 employees are less likely to increase their size in response to a positive TFPR shock in order to avoid becoming subject to the provisions of Article 18 of the Italian Workers Statute.

1.7 Aggregate Implications: Misallocation, TFP, and Lost Output

Resource misallocation has received much recent attention as an important explanatory factor of the disparity in aggregate productivity and economic growth across and within countries ([6]; [5]; [1]; [3]). In the case of Italy, the broad consensus is that the country's spectacular failure to sustain aggregate productivity growth and contemporaneous economic stagnation of the last 20 years can be attributed in large part to malfunctioning financial, labor, and product markets that jeopardized the efficiency of the allocation of resources across their different uses ([149]).[94]

In this section, we use our micro-estimates to perform aggregate counterfactual exercises that bear on the question of how idiosyncratic distortions in investment and employment policies translate into a loss in aggregate output and TFP, and how the gains from reallocation of resources evolve over time and in different sectors of the Italian economy.

94. Data from the Italian National Statistical Institute show the Italian year-on-year TFP growth was, on average, 0.05% in the decade 1997-2007, and of -0.3% between 2008 and 2013. Data available at https://dati.istat.it (access October 2017). [149] highlights the importance of frictions in labor, capital, and output markets in preventing Italian firms from effectively responding to the competitive pressures of increasingly globalized markets, and benefit from the opportunities offered by technological innovation and EU integration.

We begin by showing that, at the firm level, output could be higher if firms were able to adjust their input-demand mix to the one that closes the MRP-cost gaps at the observed market prices. For every firm-year observation, we reconstruct a counterfactual level of output (Y_{it}^{*}) that it could have produced employing K_{it}^{*} and L_{it}^{*} (equation 1.11), and contrast it with a comparable measure of output (Y_{it}) that uses the observed input demands K_{it} and L_{it}:

$$Y_{it}^{*} = e^{a_{it}} \cdot (K_{it}^{*})^{\gamma_s} (L_{it}^{*})^{1-\gamma_s} \tag{1.13}$$

$$Y_{it} = e^{a_{it}} \cdot (K_{it})^{\gamma_s} (L_{it})^{1-\gamma_s} \ , \tag{1.14}$$

where $a_{it} = va_{it} - \gamma_s k_{it} - (1-\gamma_s) l_{it}$ is the estimated firm-level valued added productivity using value added cost shares of each 4-digit industry. The value-added production function above is obviously an over-simplification of firms' production function. However, it serves our purpose. Indeed, any misspecification of firms' production process is held constant in (1.13) and (1.14).[95] Also, note that productivity and factor elasticities are held constant. Thus, the difference between Y_{it}^{*} and Y_{it} only arises from a different input mix.

We calculate the implied deviations from target output as $(Y_{it}^{*} - Y_{it})/Y_{it}$, and present their distribution in Table 1.2 and Figure 1.2 (Panel c). On average, output could be 12% higher if inputs were chosen to equalize marginal revenue products to the observed user costs. One might expect $Y_{it} < Y_{it}^{*}$ for the large majority of the observations if firm policies were somehow constrained, and if the adjustments $K_{it} \to K_{it}^{*}$ and $L_{it} \to L_{it}^{*}$ move firms close to their production possibility frontier. Consistent with this prediction, we find $Y_{it} < Y_{it}^{*}$ in

95. Value added specifications, and the corresponding estimates of productivity and elasticities are problematic from both a theoretical and an empirical point of view (see [150]). In this context, however, we are interested in reconstructing counterfactual output levels obtained using the target labor and capital (K_{it}^{*} and L_{it}^{*}), and to contrast this quantity to a comparable output level obtained using the actual input demands observed in the data (K_{it} and L_{it}).

85% of the cases. Importantly, this positive output gap does not simply result from more inputs. To see this, note that target inputs demands (either K^*_{it} or L^*_{it}, or both) are lower than firms actual input demands for 40% of the observations. That is, a significant fraction of firms in the economy could produce *more output employing fewer resources*, by simply utilizing a more efficient input-mix.

At an aggregate level, we calculate that the output produced by the Italian corporate sector as a whole would grow by 8% to 9% if firms could adjust their input demands so to close estimated MRP-cost gaps at the observed user costs.[96] These aggregate effects result from the interplay of two forces. Mechanically, output grows because - on aggregate - 7% more labor and 1% more capital is needed in the economy in order to fully close all gaps.[97] The second force generating the output gain is resource reallocation. Holding constant the aggregate endowments of capital and labor, output would grow as resources freed by negative-gap producers reach positive-gap producers.[98]

Reallocation algorithm – To isolate the output gains that can be *directly* imputed to aggregate gains in TFP driven by a more efficient allocation of the resources, we define the following counterfactual outcomes:

---

96. For every year t, we calculate the loss in aggregate output aggregating firm-specific deviations from target output $\frac{Y^*_t - Y_t}{Y_t} = \frac{\sum_i Y^*_{it} - \sum_i Y_{it}}{\sum_i Y_{it}}$. See Appendix A.12.2.

97. Appendix A.12.2 analyzes the difference between aggregate input demands in the economy ($K_t = \sum_i K_{it}$ and $L_t = \sum_i L_{it}$) and the aggregate endowments that would fully close the gaps at the observed prices ($K^*_t = \sum_i K^*_{it}$ and $L^*_t = \sum_i L^*_{it}$).

98. For the United States, [42] estimate the aggregate losses generated by binding collateral constraints at the firm-level. They find that the aggregate endowment channel matter twice as much as the misallocation channel.

$$
\begin{aligned}
Y_{it}^{**} &= e^{a_{it}} \cdot \left(K_{it}^{**}\right)^{\gamma_s} \left(L_{it}^{**}\right)^{1-\gamma_s} \\
\text{s.t.} \quad L_t^{**} &= \textstyle\sum_i m_{it}^L L_{it}^* = L_t \\
K_t^{**} &= \textstyle\sum_i m_{it}^K K_{it}^* = K_t \, ,
\end{aligned} \tag{1.15}
$$

where $m_{it}^L \gtreqless 0$ and $m_{it}^K \gtreqless 0$ are reallocation weights that meet the following criteria:

1. $m_{it}^X \geq 0$ when $\tau_{it}^X > 0$.
2. when $a_{jt} \geq a_{it}$: (i) $m_{jt}^X \leq m_{it}^X$ if ($\tau_{jt}^X \leq 0$ & $\tau_{it}^X \geq 0$); (ii) $m_{jt}^X \geq m_{it}^X$ otherwise.

The constraints in (1.15) ensure that the reallocation takes place with no change in the aggregate capital and labor endowment of the economy. The reallocation weights require resources to move in a welfare-enhancing direction: from negative MRP-cost gap producers toward positive gap firms (criterion 1), and following a productivity rank (criterion 2).[99] Appendix A.12.1 provides a detailed explanation of a reallocation algorithm that satisfies these criteria. In short, we group firms into positive and negate MRP-gaps. Then, we reallocate resources away from the lowest-TFP firm belonging to the negative-gap group, and toward the highest-TFP firms in the positive-gap group. The reallocation stops when the aggregate constraint binds ($X_t^{**} = X_t$).[100]

To study the scope of resource reallocation, we contrast Y_{it}^{**} to Y_{it} and construct our measure of aggregate out and TFP gains from reallocation as:

$$
\frac{Y_t^{**} - Y_t}{Y_t} = \frac{TFP_t^{**} - TFP_t}{TFP_t} \, ,
$$

99. Another way to restate criterion 2 is $\frac{\partial P\{m_{it}^X > 0\}}{\partial \omega_{it}} \geq 0$ if $\tau_{it}^X \geq 0$; $\frac{\partial P\{m_{it}^X < 0\}}{\partial \omega_{it}} \leq 0$ if $\tau_{it}^X < 0$.

100. Evidently, it must be the case that $X_{it}^{**} < X_{it}^*$ for some firms in the economy when $X_t^* > X_t$, and $X_{it}^{**} > X_{it}^*$ for some firms in the economy when $X_t^* < X_t$. When $X_t^* < X_t$ (not the case in our dataset), we first set $X_{it}^{**} = X_{it}^*$ for all firms, and then we reallocate the difference $X_t - X_t^*$ across firms in a way that is proportional to the relative productivity a_{it}.

Table 1.10: Aggregate implications: output and TFP gains from resource reallocation

This table presents the gains in aggregate output and TFP that accrue from resource reallocation. The reallocation algorithm is described in Section **??**. Column (1) and (2) show the percentage of capital and labor reallocated; Column (3) the implied output and productivity gains. Column (4) shows the reallocation gains when resources are reallocated without following a priority rule based on productivity.

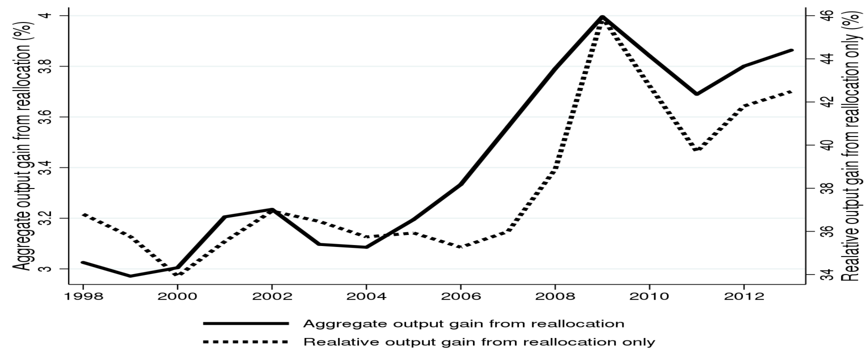
	(1)	(2)	(3)	(4)
	CAPITAL REALLOCATED	LABOR REALLOCATED	OUTPUT (TFP) GAIN	OUTPUT (TFP) GAIN
Panel a: Reallocation Within & Between Industries				
1998 - 2001	0.76 %	0.92 %	3.05 %	1.17 %
2002 - 2007	0.67 %	1.11 %	3.25 %	1.19 %
2008 - 2013	0.71 %	0.71 %	3.83 %	1.55 %
AVERAGE	0.71 %	1.14 %	3.38 %	1.30 %
Panel b: Reallocation Within Industries				
1998 - 2001	0.68 %	0.91 %	2.39 %	
2002 - 2007	0.60 %	1.10 %	2.45 %	
2008 - 2013	0.64 %	0.64 %	3.08 %	
AVERAGE	0.64 %	1.13 %	2.64 %	
Panel c: Reallocation Within Industries & Macro Regions				
1998 - 2001	0.67 %	0.91 %	1.45 %	
2002 - 2007	0.60 %	1.10 %	1.58 %	
2008 - 2013	0.64 %	0.64 %	2.24 %	
AVERAGE	0.64 %	1.13 %	1.76 %	

where $Y_t^{**} = \sum_i Y_{it}^{**}$ and $Y_t = \sum_i Y_{it}$. Because resources are reallocated with no change in the aggregate endowment, the gap between Y_t^{**} and Y_t measures output gains as well as aggregate TFP gains from reallocation.

Table 1.10 presents the output (TFP) gains that accrue from reallocation of resources from over-endowed to under-endowed producers. The solid line in Figure 1.11 provides a graphical visualization of its time-series.

Figure 1.11. Aggregate output gain from resource reallocation

This figure presents the gains in aggregate output and TFP that accrue from resource reallocation (solid line) and the relative contribution of reallocation to total output gains achievable if all gaps were closed (dotted line). The relative contribution of misallocation is calculated as the ratio of the output gains from reallocation over the total grains that would accrue if all firms could adjust their capital endowment and workforce to completely close the observed MRP-cost gaps.



Averaging across years, we find that aggregate output and TFP could be 3% to 4% higher if approximately 1% of capital and labor could be re-allocated toward high-value use producers, without changing the aggregate endowments. The dashed line in Figure 1.11 shows that reallocation alone can explain between 35% and 45% of the output gain that would accrue if producers could fully close the estimated capital and labor gaps.[101]

A number of remarks are in order. First, because productivity and factor elasticities are held constant, the difference between Y_{it}^{**} and Y_{it} only arises from a different input mix. Although firm-level productivity growth is of high interest *per se*, it is not the focus of this paper. By shutting down this channel, we focus on gains from reallocation only. Second, gains from reallocation are a function of the size of the absolute gap of firm-level distortions in capital and labor. Thus, for reallocation to have significant aggregate effects, producers with both positive and negative MRP-cost gaps must be present in the economy. Figure 1.2 shows that, indeed, both types of producers are present in our database. Finally,

101. In Appendix A.12.4 we calculate the gains from reallocation using MRP-cost gaps constructed with alternative proxies for the user costs of capital and labor ($r^{CredLines}$ and $w^{NewHires}$) and find slightly higher gains from reallocation.

our reallocation algorithm moves resources away from over-endowed and low-productivity producers toward under-endowed and high-productivity producers. This implies that, in our calculations, what matters is *both* the relative size of investment and employment distortions (i.e., the distance between K_{it}^{**} and K_{it} and between L_{it}^{**} and L_{it}) and the correlation between firm-level distortions and firm-level productivity ([5]). In the data, the correlation between distortions and productivity is positive and highly significant: within narrowly defined industries (4 digits) and years, a one-standard-deviation increase in TFPR (ω_{it}) is associated with a 0.07 and 0.16 standard-deviations increase in $\frac{(K_{it}^{*}-K_{it})}{K_{it}}$ and $\frac{(L_{it}^{*}-L_{it})}{L_{it}}$, respectively. The last column in Table 1.10 shows that by shutting down the productivity pecking order (criterion 2 of the reallocation weights), and reallocating the resources of over-endowed firms toward randomly selected under-endowed firms, the gains from reallocation would be lower by a factor of 2.

Business cycle fluctuations – The times-series evolution of $(Y_t^{**} - Y_t)/Y_t$ offers interesting insights into the importance of resource misallocation in different phases of the business cycle, and in particular during periods of credit expansion versus periods of credit crunch. We find that financial crisis periods are characterized by an increase in resource misallocation. Compared to the 1997–2004 period, gains from reallocation are 1/3 higher after the transmission of the global financial crisis to Italy (2008–2009) and the burst of the European Sovereign debt crisis that followed (2010–2013). In fact, reallocation can explain 35% of the output (TFP) gains during the 1997–2004 period, but 40%–45% of the gains during financial and sovereign crisis periods.

A substantial body of empirical evidence documents a decline in TFP during episodes of financial crisis ([36]).[102] Our findings show the strong co-integration of business-cycle

102. [36] analyzes 22 severe crises in emerging markets and finds that output and TFP typically decline by 10% and 9.5%, respectively. Examining the Chilean economy, [39] performs an analysis similar to that of [1] that documents a significant change in misallocation and consequent loss in TFP during the Chilean crisis of

fluctuations and TFP observed during episodes of financial instability might be explained, at least in part, by a deterioration of the efficiency of resource allocation ([151]; [39]; [40]). In a contemporaneous empirical study, [19] and [152] document a loss in average *firm-level productivity* of Italian corporations during the financial and sovereign crisis, and relate it to credit market frictions. Our results complement theirs, as we focus on the *reallocation channel* rather than the productivity channel.[103] Our findings are also in line with [41] who document evidence of credit misallocation in Italy during the financial crisis.

Figure 1.11 also provides interesting insights into the long-term trends in misallocation in Italy. The potential output and TFP loss due to a detrimental allocation of capital and labor across industries are relatively flat in the late 90s and early 2000s. Then misallocation starts to increase from the second half of the 2000s, reaching its peak during the financial crisis. Below, we compare this pattern with the time-series patterns obtained using alternative measures of misallocation proposed by previous literature.

Sectoral and spatial components – To better understand in which parts of the economy misallocation is generating larger output losses, we disentangle the contribution of unconstrained reallocation (between-industries and within-industries) from the contribution of within-industry reallocation, and the one of a reallocation that is constrained to take place only within the same industry and same macro-region.[104] Comparing the solid and

---

1982. [40] and [151] find a simultaneous decline of TFP and allocative efficiencies studying the Argentine Crisis of 2001 and several U.S. industries during the Great Depression.

103. [19] also use CR data and firm-level balance sheet data from Cerved, but they focuses on a subsample of larger firms. Although we adopt a different technique for production function estimation, the time-series evolution of TFPR is fully consistent across papers. For the subsample of our data that overlaps with theirs, the correlation between our measure of TFRP and theirs exceeds 85%.

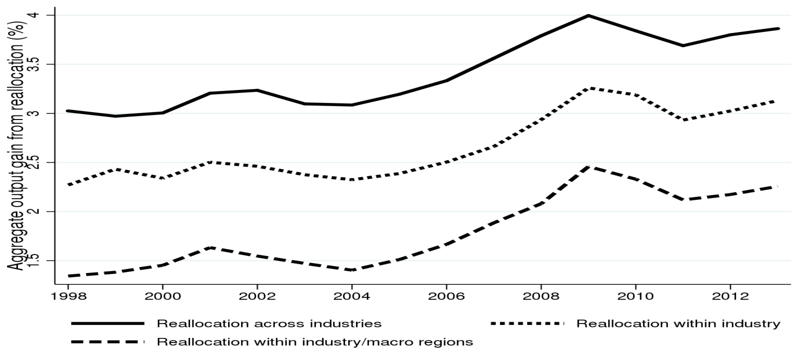
104. The reallocation algorithm adopted to construct the three aggregate measures is the same. The difference is in the level at which the aggregate constraints are required to hold. In the first case, we hold constant the aggregate amount of resources for every year ($X_t^{**} = X_t$). In the second case we do so for every 4 digits industry-year pair ($X_{st}^{**} = X_{st}$ $\forall$ industry s), in the third case for every 4 digits industry-macro-region-year pair ($X_{srt}^{**} = X_{srt}$ $\forall$ industry s and $\forall$ macro-region r).

dotted line in Figure 1.12, we find that the majority of allocative inefficiencies take place within narrowly defined 4-digit industries (roughly two-thirds).

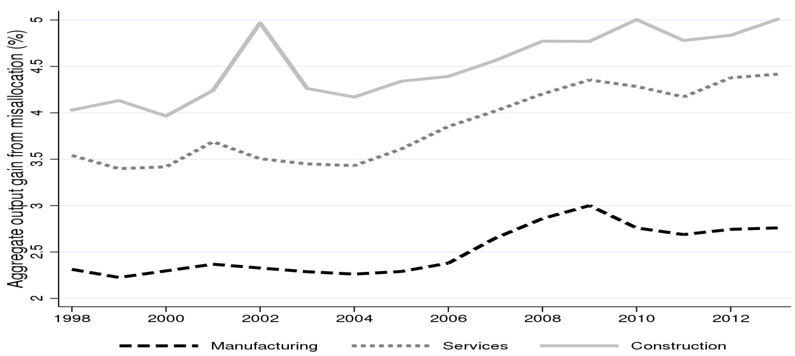
Figure 1.12. Aggregate implications: Output and TFP gains from resource allocation

This figure explores the extent of misallocation within and between industries, and across different geographical regions in Italy. Panel a presents the gains from reallocation allowing capital and labor reallocation both between and within industries (dotted line), only within 4-digits code industries (solid line), and only within 4-digits code industries/macro-regions (dashed line). Panel b presents the gains from reallocation (within 4-digits code industries) separately for each macro-industry (manufacturing, services, and construction). Panel b presents the gains from reallocation (within 4-digits code industries) separately for each macro-region (north, south, and center of Italy).

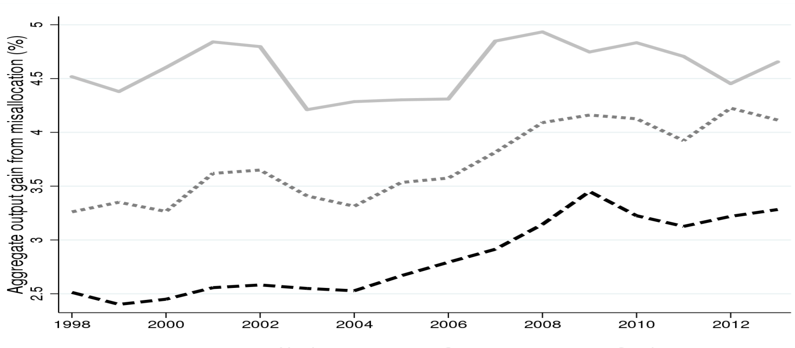
Panel a: Within versus between reallocations



Panel b: Sectoral heterogeneity



Panel c: Spacial heterogeneity



The remaining third of the welfare gain could be achieved mobilizing resources across industries ([34]). Finally, roughly two-thirds of the within-industry gains can be achieved if we constraint reallocation to take place within the same geographical macro-regions (dashed line in Figure 1.12).

Given these findings, a natural question concerns whether the scope for reallocation is similar in all industries and local markets, or rather is driven by some specific sectors or geographical regions. Figure 1.12 (Panel b) displays the output gains from within-industry reallocation for three different macro-sectors of the economy: manufacturing, services, and construction. Our estimates indicate output could grow about 2.5%–3% by improving the allocation of capital and labor among produces in manufacturing firms, 3.5%–4% in the services industry, and over 4% in the construction industry. These are novel findings. Indeed, mostly due to the lack of comprehensive data, the large majority of the empirical studies that assess the costs of misallocation focus on manufacturing industries. Considering the growing importance of non-manufacturing industries in both developed and developing economies, our analysis suggests that by extrapolating the evidence on the manufacturing sector to the whole economy, researchers might be underestimating the potential welfare losses resulting from market frictions and regulations.

Figure 1.12 (Panel c) plots output gains from reallocation for different Italian macro-regions. We previously pointed out that southern and northern regions of the country are characterized by significantly different socio-economic outcomes, which can be traced to different a historical backgrounds, quality of institutions, culture, and stock of social and human capital ([27]). For example, we highlighted the difference in terms of efficiency of bankruptcy courts between northern and southern regions of the country. In line with these observations, we find the extent of resource misallocation is significantly higher in south than in the north or center of Italy. Our estimates indicate that, without changing the amount of capital and labor in use, a better allocation of resources might rise output and productivity in Southern regions by 4.5%–5%. The scope for reallocation is lower as we move north (3.5%–4.5% in the center, and over 2.5-3.5 percent in the north), although, interestingly, the post-2004 rise in misallocation seems to be driven by these regions, whereas no upward trend is observed for southern regions.

A number of remarks are due. First, we must note that the reallocation of capital and labor across producers is expected to have an impact on the level and distribution of factor prices, even when the aggregate amount of capital and labor in the economy does not change. Our analysis does not consider these important general equilibrium effects. In general, the direction and magnitude of these effects depend on the characteristics of the firms from and to which resources are mobilized. Second, our sample includes only incorporated firms. Thus, there is a question related to the generalization of the previous results to the whole Italian economy. Due to their smaller size, greater opacity, and lack of managerial capital, the non-corporate sector may exhibit investment and employment policies more distorted than the ones we found for the limited liability firms in our database ([140]). Thus, our calculations might understate the scope of misallocation in the whole economy. Finally, we shall emphasize that our exercise takes the set of producers as given. Thus, it does not account for a particular form of misallocation that has to do with the pool of producers that end up operating (selection effect).[105]

Alternative measures of misallocation – We conclude this section with a comparison of our estimates of allocative efficiency gains to alternative measures adopted in the literature. Figure A.15, Panel a, in Appendix A.12.3 presents the time-series evolution of the OP-covariance term ([153]), that is, the correlation between firm-level productivity (ω_{it}) and local market share (Revenues$_{ispt}$/$\sum_i$Revenues$_{ispt}$, s=industry and p=province). Although this indicator of allocative efficiency displays pretty large variability over time,

105. [139] and [140] highlight the importance of financial friction on the extensive margin.

we obtain a significant steady decline of it starting in 2005, which is consistent with the gradual increase in gains from reallocation shown in Figure 1.11. Panel b of Figure A.15 displays the within-industry standard deviation of $ln(MRP^K)$ and $ln(MRP^L)$. Starting from the seminal work of [1], the dispersion of marginal revenue products has been largely used in cross-country analyses because, under specific model assumptions, it is proportional to the dispersion in TFPR which, in turn, is inversely proportional to the efficiency of within-industry resources allocation. Consistent with our measures, we find that dispersion in both Marginal Products is increasing over time, particularly for capital and especially during the financial and sovereign crisis.[106] Panel c of Figure A.15 plots inferred allocative efficiency for Italy, calculated by taking to the data the model in [154] (BKR). Consistent with our results, the BKR procedure highlights a downward trend in the allocative efficiency starting in 2005. Finally, in Panel d, we plot the average absolute deviation from target output ($\sum_i \frac{1}{N_t} |(Y_{it}^* - Y_{it})/Y_{it}|$, where N_t is the number of observations in year t) across the different years of our sample. This measure, inspired by the measure of allocative efficiency developed by Amil Petrin and coauthors ([32]; [155]; [13]), correlates strongly with the economic downturn of early 2000s, and it confirms the aggregate dynamics obtained with our reallocation algorithm starting in 2005.[107]

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106. An influential study by [38] (GKKV, henceforth) looks at the dispersion of log MRP to investigate the extent of misallocation in Europe, arguing that the productivity slowdown in Spain, Italy, and other Southern European countries may have been driven by the credit expansion that followed the establishment of the European Monetary Union. For Italy, the data source for the accounting variables used by GKKV is ultimately the Cerved database, in its release by Bureau Van Dijk. Thus, it is reassuring that the trends in log-MRP^K and log-MRP^Ldispersion we obtain are very similar to those of GKKV, with a particularly remarked upward trend for capital. We shall emphasize, however, that the time series of the dispersion of log-MRP^L differs from the one in GKKV: downward in their paper, but upward in our data. This is likely due to the fact that we measure labor services in effective units, while the authors use the total wage bill.

107. In a sequence of papers, Amil Petrin and coauthors ([32]; [155]; [13]) have proposed measures of allocative efficiency based on the aggregation of firm-level gaps between a firm Value of the Marginal Products and factor prices (VMP-cost gaps). They theoretically demonstrate that the integration of VMP-cost gaps provides us with a direct estimate of Aggregate Productivity Growth (APG) in the spirit of [156] and [157].

1.8 Concluding Remarks and Future Research

In this paper, we combine information on firm-specific borrowing costs and wages with estimates of the marginal returns to produce empirical measures of deviations in firms' first-order conditions. The analysis of the distribution and variation of MRP-cost gaps provides valuable insights into the impact of credit and labor market frictions on firm policies, and into the aggregate implications of resource misallocation in terms of output and aggregate productivity loss. Our approach is capable of guiding researchers toward the primitive frictions affecting firm policies and can be used to test the effects of policy interventions that economists want to confront directly with the data. Because they require no information on the firm market value of assets or liabilities, MRP-cost gaps are a particularly valuable tool to study investment and employment policies of privately owned firms, for which standard empirical measures are unavailable.

The natural extension of our analysis is the estimation of a fully-fledged dynamic structural model that, by using MRP-cost gaps as additional moments to target in the estimation, can further cast light and disentangle the impact of other market frictions such as taxes, moral hazard behavior, or uncover the implicit cost of equity financing for private firms. With this respect, a key modeling issue is to incorporate the effect of frictions and regulations on endogenous decisions that affect future realizations of firm-level productivity.

The procedure that calculates the aggregate output and TFP gains from a more efficient allocation of resources is transparent and intuitive, but does not consider the general equilibrium effects on the level and distribution of interest rates and wages that may result from reallocation. In the future, it would be interesting, and important, to incorporate these general equilibrium spillovers, without neglecting the heterogeneity across producers and its micro-foundation ([158]).

APPENDIX A

A.1 Data Appendix

A.1.1 Data Sources and Variables Description

Balance sheet, income statement, and registry variables – Information on firms' balance sheet, income statement, and location comes from a proprietary database assembled by the Cerved Group S.p.a.. When firm age is not available from Cerved or from the National Security Institute, we use the information from the Italian Firm Registry (InfoCamere database). Table A.1 (panel a) describes the variables collected from Cerved and Italian Firm Registry.

Relationship-level variables – Using unique firm identifiers we merge the firm-level dataset with the Italian Credit Registry (CR) administered by the Bank of Italy. The CR provides us with detailed, confidential information on the credit relationships entertained by the firms in our database with all intermediaries operating in Italy. Through the Central Credit Registry financial companies supervised by the Bank of Italy exchange information about the global risk position (outstanding credit and credit in default) of their customers and of those of other institutions. After it receives information on the loans granted by the participating intermediaries to individual customers, the Bank of Italy aggregates the data for each borrower and calculates its total debt exposure vis-a-vis the financial system, and possible amounts past due or in default. This information, called the "global risk position", is anonymized (no lender identifier) and made accessible to all intermediaries for a small fee.

Table A.1 (panel b) summarized the list of the variables from CR. At a monthly frequency, we collect data on the outstanding stock of bank debt of each borrower vis-a-vis each financial institution between January 1997 and December 2013. CR distinguishes between three different types of bank debt: term loans, loans backed by account receivables (credit BBR), and revolving credit lines. For each type of product, we are able to observe the amount granted by the institution and the amount of credit effectively used by the customer. We aggregate this data at the firm-year-level as follows. For each firm-bank relationship we calculate the average balance during the year and then sum across all relations. We do this for the total amount (granted) of bank debt (CREDIT_{it}= term loans + loans BBR + lines of credit), the total amount of loans (LOANS_{it}= term loans + loans BBR), and credit lines (CREDIT LINES_{it}): i.e. X_{it}=$\sum_{b\in\mathcal{N}_{it}^{B}}(\frac{1}{12}\sum_{m=1}^{12}X_{ibmt})$, where X={CREDIT, LOANS, CREDIT LINES} and $\mathcal{N}_{it}^{B}$ is the set of lenders of banks in year t.

Exploiting the panel dimension of CR, we measure the length of the lending relationship between a borrower and each of its lenders. For each firm-bank pair, we count the number of months of continuous credit interactions (i.e. months with outstanding debt in the CR). We denote this variable by Length $\text{Relationship}_{ibt}$. For relationships already in place in January 207 (first month-year in our sample), we conventionally set the beginning of the relation to Jan 2007. Thus, Length $\text{Relationship}_{ibt}$ has support between zero (no credit relationships) and 16 years (credit relationship in place for every quarter between January 1997 and December 2013). Then, we compute three firm-level proxies of duration of the lending relationships of a firm in any given year.

Let $\hat{m}$ denote the month-year in which a credit relationship between a firm and a financial institution is established (i.e. we observe a positive outstanding credit balance in the Credit Registry between the two parties). Ever $m > \hat{m}$ we count the number of months of continuous credit relationship between the pair. For lending relationships already in place at the beginning of our sample, we set $\hat{m} = Jan1997$. Then the length of the relationship between firm i and bank b in measured in year t is Length $\text{Relationship}_{ibt}$ the total number of months since $\hat{m}$. We compute three variables that aggregate Length $\text{Relationship}_{ibt}$ at firm-year level. First, we calculate the average length of the lending relationships as the arithmetic average across all relationships (LENGTH RELATIONSHIP$_{it}^{mean}$ = LENGTH RELATIONSHIP$_{ibt}$/ NUMBER RELATIONS$_{it}$. Second, we calculate the weighted average across relationships using the share of debt provided by each lender as weight (LENGTH RELATIONSHIP$_{it}^{wmean}$ =$\sum_{b\in\mathcal{N}_{it}^{B}} s_{ibt}^{B}\cdot$LENGTH RELATIONSHIP$_{ibq}$, where $s_{it}^{B} = \frac{Credit_{ibt}}{\sum_{b\in\mathcal{N}_{it}^{B}} Credit_{it}}$). Third, we calculate the length of the relationship with the most important lender (highest s_{it}^{B}) of the bank intermediary (LENGTH RELATIONSHIP$_{it}^{lead}$). These three variables are rescaled to measure the length of relations in years (or fractions of years). Every year, we define the variable NUMBER RELATIONS$_{it}$ that counts the number of active credit relations between a firm and its lending institutions during year t.

Using information on credit defaults (bad loans) and debt restructuring events from the CR, we define a variable DEFAULT$_{it+1}$ which is equal one if the firm displays any amount of debt in default, restructured, or being restructured in period $t+1$. We also define a dummy variable that indicated whether the firm displays any amount of debt in default, restructured, or being restructured in year $t' \leq t$ (DEFAULT EVER BEFORE$_{it}$).

Finally, we measure bank leverage as: BANK LEVERAGE$_{it}$=CREDIT$_{it}$/ TOTAL ASSETS$_{it}$.[108]

We collect information on interest rates charged by a large, representative sample of banks to Italian borrowers. These data are included in the Taxia database, a sub-section of the Credit Register that covers over 80% of the total credit issued by the Italian banking system. Mirroring the Credit Registry, Taxia collects relationship-level information on the Annual Percentage Rate on bank loans, credit lines, and credit BBR. When multiple loans, credit lines, or loans BBR are observed for a bank-firm pair during the same period, we cal-

108. For a limited number of observations we observe some bank debt reported in the balance sheet, but these credit relations do not appear in the CR; or we find that the total amount of bank debt from CR is lower than the amount reported in the balance sheet. In this case, we define: BANK LEVERAGE$_{it}$=max{BANK DEBT$_{it}$,CREDIT$_{it}$}. See below for a discussion of these observations.

culate the average APR using the inverse of the nominal amount paid as interest as a weight. Every year, we calculate a firm-level APR as the value-weighted average of the APR paid to different lenders, with weight equal to the share of bank loans provided by each financial institution: $r_{it+1} = \sum_{b \in \mathcal{N}_{it}^{B}} w_{ibt} r_{ibt+1}$, where $w_{ibt} = \text{LOANS}_{ibt} / \sum_{b \in \mathcal{N}_{it}^{B}} \text{LOANS}_{ibt}$.[109] We follow a similar procedure in the calculation of the APR on credit lines $r_{it+1}^{CredLines}$, using as weights $w_{ibt} = CredLines_{ibt} / \sum_{b \in \mathcal{N}_{it}^{B}} CredLines_{ibt}$.

Table A.1 (panel c) summarizes the variables collected from the CR.

Employment and wages – The records from the Italian National Security Institute (INPS) provide us with detailed information on firms' workforce composition and compensation. The INPS database is composed of two sub-datasets. The first is a firm-level database that covers the entire population of private firms with at least one employee. For these firms, INPS provides the average monthly paid by the firm to all its employees, and the average monthly wage by workers' category (white collars, blue collars, middle managers, and full-time interns). The INPS data also provides us with information on the number of full-time employees employed by the firm during each month, and the average number of employees by workers' category. For each firm-year observation, we calculate the average monthly wage and average monthly number of employees, and then annualize them. We round the annualized number of employees to the largest integer.

The second database from INPS is an employer-employee matched database. This dataset follows the employment history of a random sample of 20% of every cohort of workers. Using individual wage records, we calculate the average annualized wage paid by firms to *newly hired* workers. Then we calculate the average wage paid by newly hired

109. When a firm has both term loans and loans backed by receivables, and we observe the interest rate for both of them, we use the interest rate on term loans for the calculation as r_{ibt+1}.

workers for each industry-province-year triplet. Table A.1 (panel a) describes the variables collected from INPS.

Length of bankruptcy litigations in court – Using data from the Italian Ministry of Justice, we collecting information on the average length of bankruptcy trials. For every Italian province, we calculate the average length of bankruptcy litigations between years 2005 and 2007 (LENGTH BANKRUPTCY). We exclude from our sample the province of Naples because a careful inspection of the data reveals poor data quality. We are also unable to collect information for the province of Reggio Nell'Emilia. Figure A.1, panel a illustrates how the length of bankruptcy litigations in court vary across provinces and across different macro-regions (North, Center, and South of Italy). Panel b focuses on within-macro-region variation. For each macro-region, it displays the length of bankruptcy litigations of each province, as a deviation from the average length in the macro-region.

Other variables – We collect a number of variables from the website of the Italian National Statistical Office. We collect data on 2-digits industry-specific price deflators (output deflator, value added deflator, and CPI), 2-digits industry-specific depreciation rates of fixed assets.[110] Also, we collect the following set of socio-economic indicators measured at the province level in year 2007: population, GDP, unemployment rate, active firms per resident, firm exit rate, Herfindahl-Hirschman Index of credit market concentration, and the number of active credit institutions. RZ Index is the [159] index of dependence on external finance.

110. To obtain industry-specific depreciation rates of capital, we use time-series data on amortizations and net capital stock by two-digits Nace Rev.2 from the Italian National Accounts. We calculate the ratio of amortizations to net fixed capital in each year between 1970 and 2014 for each industry. For each two-digits Nace, we construct the industry-specific depreciation rates as the time-average of this ratio. The ratio between amortizations and net fixed capital displays little year-to-year variation. Thus, using the time-average of this ratio, rather its time-year value has little impact on our series of firm-level capital constructed using the PMI method. Our results are unaffected by this choice.

A.1.2 Winsorization

We winsorize the 0.5% tails of the variables from Cerved, the CR, and the Social Security administration. We winsorize the 2.5% tails of our estimates of marginal revenue products, output elasticities, markups, productivity, MRP-cost gaps, and percentage deviations from target input demands and output. All winsorizations are done after the construction of MRP-cost gaps and of the respective percentage deviations.

A.1.3 Reporting Thresholds and Sample Changes in the Credit Registry and Taxia database

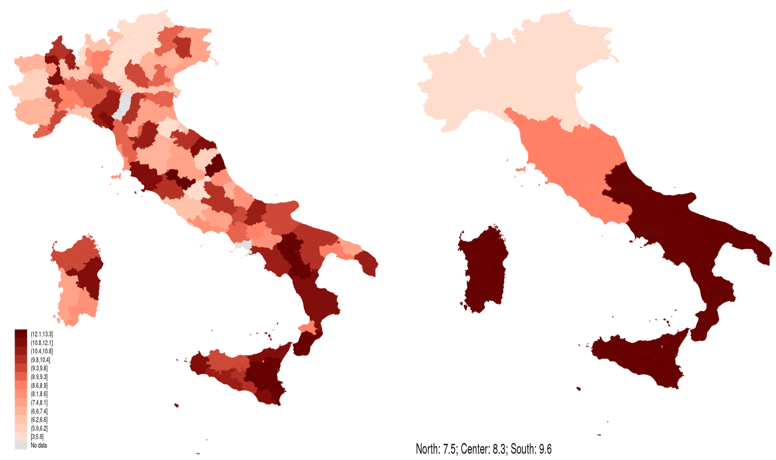
During our sample period, there have been two regulatory changes that affected the sample of firms in the CR and Taxia database. Between 1997 and 2008, intermediaries under the supervision of the Bank of Italy are required to report to the CR any lending relationship *in bonis* whose sum of outstanding credit plus guarantees exceeds 75 thousand Euros. Starting from January 2009, the reporting threshold has been lowered to 30 thousand Euros.

The second change affected the number of relationships for which we have information on interest rates. The Taxia database covers the lion-share of the financial intermediaries operating under the supervision of the Bank of Italy. Until 2003, the subgroup of banks in Taxia was composed by around 90 banks, accounting for more than 80 percent of total bank lending. Starting from 2004, the pool of bank in Taxia has been expanded to 103 Italian banks and 10 branches and subsidiaries of foreign banks. Banks in the Taxia sample must report information on the APR charged to every borrower if the total amount of credit granted plus guarantees provided by the borrower exceeds 75,000 euro.

To investigate the impact of these reporting thresholds and their evolution over time, we group observations into 4 types of firms, depending on whether we observe their debt

Figure A.1. Variation in bankruptcy litigations

Panel a: Variation Across Provinces (left) and Across Macro Regions



Panel b: Variation Within Macro Regions

Northern Italy | Central Italy | Southern Italy

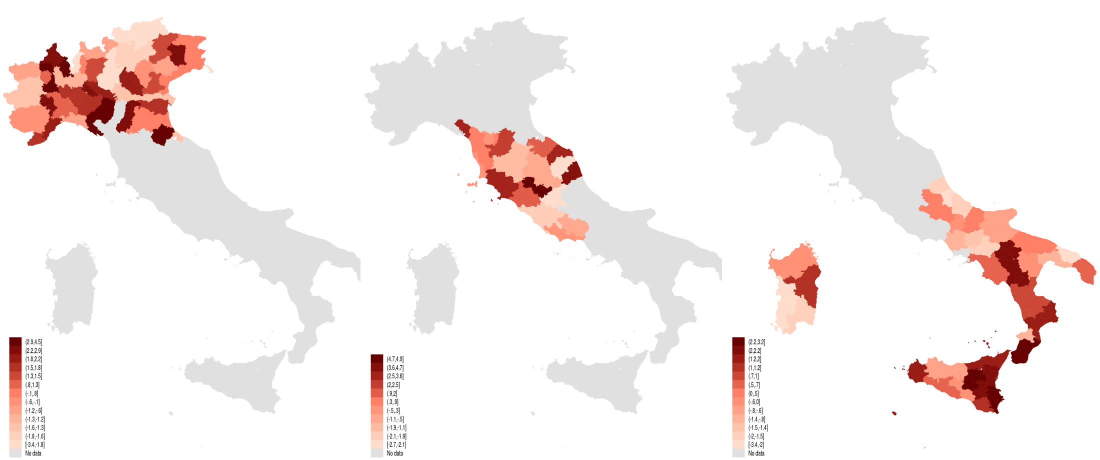


Table A.1: Codebook of variables

Panel a: Balance sheet, income statement, and registry variables (Cerved database and Italian firm registry)

Variable	Description	Units	Source
REVENUES$_{it}$	Revenues (sales)	Thousand Euros	Cerved
WAGE BILL$_{it}$	Wage bill	Thousand Euros	Cerved
MATERIALS$_{it}$	Total cost of intermediate inputs (materials and services). Materials are net of changes in inventories	Thousand Euros	Cerved
TOTAL ASSETS$_{it}$	Total assets	Thousand Euros	Cerved
BOOK VALUE K$_{it}$	Book value of tangible and intangible fixed assets	Thousand Euros	Cerved
INVESTMENTS$_{it}$	Investments in tangible and intangible fixed assets	Thousand Euros	Cerved
DIVESTMENTS$_{it}$	Sales of tangible and intangible fixed assets	Thousand Euros	Cerved
AGE$_{it}$	Firm age	Years	Cerved/INPS/Firm Registry
PROVINCE$_{i}$	Headquarter province	String	Cerved
INDUSTRY$_{i}$	Unless specified otherwise, 4-digits NACE Rev. 2 industry codes	Numeric	Cerved
CREDIT SCORE$_{it}$	Altman's Z-score is constructed from balance sheet variables by the Cerved Group following the methodology proposed by [69] and [70]. The Z-score ranges from 1 to 9, with lower numbers (1 to 4) indicating high solvency low risk; higher numbers (7 to 9) indicating troubled economic and high risk.	Numeric	Cerved
EBITDA$_{it}$	Earnings before interest, tax, depreciation and amortization	Thousand Euros	Cerved
ROA$_{it}$	Return on assets	Numeric	Cerved
ASSETS TURNOVER$_{it}$	REVENUES$_{it}$ / TOTAL ASSETS$_{it}$	Numeric	Cerved
CASH FLOWS / Assets$_{it}$	CASH FLOWS$_{it}$ / TOTAL ASSETS$_{it}$	Numeric	Cerved

Table A.1 (cont'ed): Codebook of variables

Panel b: Relationship-specific variables (Credit registry)

Variable	Description	Units	Source
BANK LOANS$_{it}$	Total bank loans granted by financial institutions.	Thousand Euros	CR
CREDIT LINES$_{it}$	Lines of credit granted by financial institutions	Thousand Euros	CR
CREDIT BBR$_{it}$	Credit backed by receivables granted by financial institutions	Thousand Euros	CR
NUMBER RELATIONS$_{it}$	Number of institutions with which the firm has active lending relations	Numeric	CR
DEFAULT$_{it+1}$	Dummy equal 1 if any bank credit in default, credit restructured, or being restructured in $t+1$	Numeric	CR
EVER DEFAULT BEFORE$_{it}$	Dummy equal 1 if any bank credit in default, credit restructured, or being restructured in any $t' \leq t$	Numeric	CR
LENGTH RELATIONS$^{mean}{}_{it}$	Average length of lending relationships with financial institutions	Years	CR
LENGTH RELATIONS$^{wmean}{}_{it}$	Weighted average length of lending relationships with financial institutions	Years	CR
LENGTH RELATIONS$^{lead}{}_{it}$	Length of relation with most important lender	Years	CR
LEVERAGE$_{it}$	BANK DEBT$_{it}$ / TOTAL ASSETS$_{it}$	Numeric	CR/Cerved
r_{it+1}	Value weighted average Annual Percentage Rate on loans granted by financial institutions	Percentage	TAXIA
$r_{it+1}^{CredLines}$	Value weighted average Annual Percentage Rate paid on credit lines draws	Percentage	TAXIA

Panel c: Employment and wages (Italian national social security institute)

Variable	Description	Units	Source
EMPLOYEES$_{it}$	Average number of paid full-time employees over the year	Heads	INPS
w_{it}	Average yearly wage paid to full-time employees	Thousand Euros	INPS
$w^{NewHires}{}_{it}$	Province-industry-year average yearly wage paid to newly hired workers	Thousand Euros	INPS

in CR or in their balance sheet, the type of product they use (loans vs credit lines), and whether we have information on the APR on loans.

- *Group 0* - BORROWERS-LOANS. Firms that have outstanding loans with banks in the Taxia database
- *Group 1* - BORROWERS-NOLOANS. Firms that have outstanding credit lines with banks in the Taxia database, but no outstanding bank loans
- *Group 2* - BORROWERS-NOTAXIA. Borrowers that appear in the Credit Registry, but for which we observe no information on their APR on loan because their lender(s) do not belong to the group of banks that form the Taxia sample, or because credit has been granted but not yet utilized by the firm.
- *Group 3* - BORROWERS-NOCR. Borrowers with no outstanding debt obligations that appear in the Credit Registry, but that report positive bank debt on their balance sheet.
- *Group 4* - NON-BORROWERS. Firms that have not outstanding debt obligations (neither in the CR nor in their balance sheet).

We define a dummy variable BORROWER that takes value one for firms in Groups 0 to Group 3. Borrowers amount in total to 80 percent of the observations in our sample. 91 percent of firms borrowed at some point during our sample period.

Table A.5 (panel a) reports the fraction of observations belonging to each group by year. Looking at the composition of the sub-sample of borrowers, for 65 percent of the firms we observe outstanding loans and have information on their APR (Group 0). Only 7 percent has ho outstanding loans but open credit lines (Group 1).

For 18 percent of borrowers, we have no information on interest rates (Group 2). Two types of observations fall into this category. First, firms borrowing from banks that do not belong to the Taxia sample. Second, the group also includes firms for which the APR can not be calculated because the Credit Registry reports a positive amount of credit granted, but this credit is not yet utilized (about 6% of this Group 2 firms).[111] In 2004, following the expansion of the pool of banks in the Taxia sample, we observe a drop in the percentage of observations in Group 2. Consistently, the large majority of these observations migrated into Group 0.

Finally, 10 percent of borrowing firms report some bank debt in their balance sheet but it does not appear in the Credit Registry (Group 3). For this group of firms, the value outstanding obligations vis-a-vis each individual lender does not exceed the reporting threshold of the Credit Registry. As discussed, the threshold was reduced in 2009.[112] Consistent with the change in threshold, we observe a significant drop in the number of firms in Group 3 from 2009. The large majority of these firms migrate into Group 2 (rather than Group 0), which suggest that this type of firms tend to borrow from smaller banks or other lending institutions that are not commercial banks.

Approximately 20 percent of the firms belong to Group 4 (BORROWER=0). This percentage decreases over time, as more credit flew into the Italian economy.

Table A.5 (panel b) reports descriptive statistics for the 5 subsample of firms. A number of observations are in order. Moving from Group 0 to Group 5, firms become smaller and younger. Their credit rating deteriorates, and firms are also more likely to operate outside manufacturing and to be located in the Southern regions of the Italy, which are characterized by less efficient credit markets and institutions. The duration of lending

111. Among this group of firms, 90 percent reports outstanding loans and 10 percent only credit lines.

112. For this subsample of firms, the median amount of bank debt reported in the balance sheet is 8 thousand Euros; the 90th percentile is 39 thousand Euros.

Table A.5: Credit market participation

Panel a: Sample Composition

	As a share of tot. number of borrowers: Borrower Loans (*Group 0*)	Borrower NoLoans (*Group 1*)	Borrower NoTaxia (*Group 2*)	Borrower NoCR (*Group 3*)	Share of Non-Borrower (*Group 4*)	Observations
1997	0.65	0.05	0.14	0.08	0.24	152420
1998	0.67	0.05	0.14	0.07	0.24	157044
1999	0.67	0.04	0.15	0.06	0.25	166630
2000	0.68	0.04	0.15	0.06	0.25	177974
2001	0.69	0.04	0.16	0.05	0.26	190056
2002	0.62	0.03	0.16	0.13	0.20	203780
2003	0.61	0.03	0.17	0.14	0.20	213687
2004	0.70	0.03	0.10	0.14	0.20	225340
2005	0.70	0.03	0.10	0.14	0.21	236928
2006	0.70	0.03	0.10	0.14	0.21	248101
2007	0.71	0.03	0.11	0.13	0.21	262749
2008	0.70	0.03	0.11	0.14	0.20	272152
2009	0.64	0.02	0.26	0.05	0.16	278703
2010	0.63	0.02	0.26	0.06	0.17	283024
2011	0.62	0.02	0.27	0.06	0.18	288962
2012	0.60	0.02	0.28	0.08	0.19	290426
2013	0.58	0.02	0.29	0.08	0.21	285233
1997-2013	0.65	0.03	0.18	0.10	0.20	3933209

Note: Standard errors of the sample mean reported in parenthesis.

relationships also decreases, partially reflecting the younger age of the firms as we move from Group 0 to group 4.

A.1.4 Sample Selection

1. We drop firms with two or more years of discontinuous (missing) balance sheet information.[113]

2. We drop observations with non-positive revenues and assets; a careful inspection of these cases revealed that they refer to firms in default or liquidation, that still file a formal balance sheet despite their real economic activity has effectively chased.

113. The two discontinuous years could be consecutive or not. This allows us to keep a sample of firms for which we observe an uninterrupted time-series, and for which clean accounting data is available.

Table (cont'ed): Credit market participation

Panel b: Credit Market Participation by firm characteristics

	BORROWER LOANS (*Group 0*)	BORROWER NOLOANS (*Group 1*)	BORROWER NOTAXIA (*Group 2*)	BORROWER NOCR (*Group 3*)	NON-BORROWER (*Group 4*)
TOTAL ASSETS	4901.05	2284.92	1990.74	979.76	651.12
	(8.71)	(26.35)	(10.71)	(11.10)	(3.80)
REVENUES	5334.63	2891.48	2303.54	1088.36	814.72
	(9.41)	(31.33)	(12.04)	(11.79)	(4.22)
AGE	14.99	12.95	10.89	7.59	8.17
	(0.01)	(0.04)	(0.01)	(0.01)	(0.01)
CREDIT RATING	5.50	5.47	5.04	6.07	5.26
	(0.00)	(0.02)	(0.01)	(0.01)	(0.01)
ROA	0.03	0.02	0.03	0.00	0.02
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ASSETS TURNOVER	1.31	1.79	1.52	1.60	1.78
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
CASH FLOW / TOTAL ASSETS	0.04	0.02	0.05	0.01	0.04
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
BANK LEVERAGE	0.66	0.36	0.40	0.16	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
BANK LOANS / BANK DEBT	0.79	0.00	0.64	-	-
	(0.00)	(0.00)	(0.00)	(-)	(-)
NUMBER RELATIONS	4.82	1.89	1.92	-	-
	(0.00)	(0.00)	(0.00)	(-)	(-)
BANK LEVERAGE^{wmean}	4.12	3.51	2.85	-	-
	(0.00)	(0.01)	(0.00)	(-)	(-)
MANUFACTURING	0.42	0.09	0.24	0.16	0.15
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SERVICES	0.43	0.73	0.59	0.67	0.66
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CONSTRUCTION	0.15	0.18	0.17	0.17	0.19
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
NORTHERN REGIONS	0.65	0.49	0.52	0.42	0.37
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CENTRAL REGIONS	0.20	0.25	0.25	0.26	0.27
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SOUTHERN REGIONS	0.15	0.26	0.23	0.32	0.35
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
OBS. (% TOTAL)	52.09	2.22	14.47	7.60	20.42

NOTE: STANDARD ERRORS OF THE SAMPLE MEAN REPORTED IN PARENTHESIS.

3. We drop firms with missing information on age, industry, headquarter province. We also drop firms whose headquarter is located outside of the country.

4. We drop firm-year observations that we were unable to match with the workforce database from the Italian National Security Institute. This selection step drops firms with no paid employees. These firms include corporations whose only workers are owners, corporations whose workers are hired through a contractor, and potential mismatches between the company's fiscal code provided to INPS and the company's fiscal code provided to Cerved.

5. We also drop observations referring to firms operating in the following Nace rev.2 two-digits industries: Agriculture (NACE 1-3), Mining and quarrying (NACE 5-9) Utilities (NACE 35-39), Postal Services and Courier Activities (NACE 53), Scientific activities and R&D (NACE 72), Public administration and National defense (NACE 84), Education (NACE 85), Health services (NACE 86-88), Sport, Arts, Entertainment Activities, and Activities of membership organizations (NACE 90-4), Activities of households as employers (NACE 97 and 98), and Activities of extraterritorial organizations and bodies (NACE 99) to avoid dealing with firms with complete, or partial government ownership or heavily subsidized by the government, and/or because it is difficult to measure output for these sectors; Financial and insurance activities (NACE 64-66) and Real estate activities (NACE 68) because firms operating in these industries are themselves credit provides, and because it is difficult to measure output for these sectors. We also drop Tobacco (NACE 12), Pharma (NACE 21) because multinational companies are the most important players in these industries.

6. Then, we keep only firm-year observations for which we can compute the marginal revenue product of capital and labor.[114]

A.1.5 Additional Summary Statistics

Table A.6 presents additional summary statistics on the variables used as controls in the regression. It provides information on the distribution (deciles) of the distribution of age, assets, revenues, and length of lending relationship (weighted average, and length of the most important relationship).

A.1.6 Construction of Time-series of Fixed Assets with the Perpetual Inventory Method (PIM)

We reconstruct the sequence of the flow of service of capital using the Perpetual Inventory Method (PIM) ([96]).[115] The idea of PIM is to interpret the firm capital stock as an inventory, which increases after new capital investments (capital purchases) and decreases over time due to depreciation and/or disinvestments (capital sales). Absent disinvestments, new capital that enters the firm remains forever and provides production services whose economic value decays over time. While the value of the investment decreases in the course of time, it never falls to zero. Thus, an investment principally has a perpetual use. Assuming geometric depreciation at a constant rate δ, we recursively calculate the time series of perpetual assets of the firm as follows:

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114. See Section **??** for our measure of the marginal revenue product of capital and labor.

115. See [160] for a review of alternative implementations of the Perpetual Inventory Method.

Table A.6: Additional summary statistics

Deciles	AGE	ASSETS	REVENUES	LENGTH CREDIT RELATION^{wmean}	LENGTH CREDIT RELATION^{lead}
1	1	74.6	83.9	0	0
2	2	167.3	197.8	1	1
3	3	271.0	321.5	1	1
4	5	405.3	478.8	2	2
5	6	590.4	692.0	2	2
6	9	859.1	999.4	3	3
7	12	1285.5	1480.7	4	4
8	17	2064.6	2357.1	5	5
9	23	3968.0	4471.3	7	8
10	38	22779.2	24898.9	10	12

$$K_{i\tau} = (1-\delta)^{\tau-1} K_{i0} + \sum_{t=0}^{\tau-1} (1-\delta)^t \left[I_{i\tau-(t+1)} \right]$$

where τ denotes the number of years since firm i's incorporation, and K_{i0} is the initial capital stock. To apply the Perpetual Inventory Method, we need (i) a time series of investment data, (ii) information on the initial capital stock at the time when the investment time series starts (i.e. the average age of the starting value of capital) and (iii) information on the rate of depreciation of the existing capital stock. The time-series on investment data comes from the Cerved database. We use net investments (INVESTMENTS$_{it}$ minus DIVESTMENTS$_{it}$). We rely on the first observable value of firms' net book value of fixed assets from the Cerved database (BOOK-VALUE K$_{it}$ minus FUND AMORTIZATION$_{it}$) to obtain the initial value of capital for the PIM algorithm, use the investment deflator of that year to produce the deflated series used in the production function estimation.[116] Both tangible and intangible fixed assets are accounted in the initial value K_{i0} and in the net investment flows. Depreciation rates come from the Italian National Statistical Office (see Section "Data sources and variables description").

116. We use the entire Cerved sample (1982-2014) for the construction of the capital series using the PIM, despite the fact that our analysis uses only the subsample 1997-2014. This is important because the precision of the PIM improves as the firm grows older and we move away from the initial K_{i0}. We also experimented with alternative methods that impute year of assets acquisition used to deflate assets that are based on the industry-specific lifecycle of fixed assets, and find very similar series of PIM capital.

A.2 Credit Market Participation and Loan Pricing

A.2.1 Bank loans, Credit Lines, and Investments

This section shows that changes in terms loans are positively and highly correlated with changes in capital expenditures (investments in fixed assets). Table A.7 shows the elasticity of different types of credit on investments. In Panel a, we control for year and industry fixed effects. Panel b controls form year and firm fixed effects. Column (1) considers all bank credit (loans + credit lines); Column (2) and (3) consider separately loans and credit lines; Column (4) runs a horse-race between the two. Standard errors are clustered at firm-level. We find that increments of both forms of credit are positively correlated with changes in the capital expenditures, but the elasticity with respect to loans is 3 times as high. In the horse-race regression, changes have an economically negligible effect on the residual variation of investments once we augment the regression with firm fixed effects. These results suggest that bank loans are the main source of bank financing for investments in fixed assets. Credit lines are an important source of financing for firms ([161]), but they mostly finance working capital rather than fixed assets. This provides empirical support for our choice of the APR on bank loans as relevant interest rate to measure the cost of debt incurred by firms when they finance capital expenditures.

A.2.2 Inferring Missing Interest Rates on Bank Debt

We adopt the following econometric procedure to infer missing information on the price of bank debt (APR on term loans) possibly faced by individual firms. We estimate the following linear regression model in the bank-firm matched dataset:

Table A.7: Elasticity of fixed assets with respect to different types of credit

Panel a: Between firm regressions

	(1)	(2)	(3)	(4)
	Ln(K_{it+1})			
Ln(Credit$_{it}$)	0.397			
	(0.002)			
Ln(Loans$_{it}$)		0.440		0.480
		(0.001)		(0.002)
Ln(Credit Lines$_{it}$)			0.150	0.031
			(0.001)	(0.001)
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
adj.R2	0.420	0.450	0.240	0.486
Obs	2574315	2389490	2201094	2016268

Panel b: Within firm regressions

	(1)	(2)	(3)	(4)
	Ln(K_{it+1})			
Ln(Credit$_{it}$)	0.113			
	(0.001)			
Ln(Loans$_{it}$)		0.121		0.139
		(0.001)		(0.001)
Ln(Credit Lines$_{it}$)			0.028	0.011
			(0.000)	(0.000)
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
adj.R2	0.907	0.908	0.904	0.910
Obs	2504057	2323294	2130257	1949789

$$r_{ibt+1} = \beta_0 + \quad \beta_1 ROA_{it} + \beta_2 Assets\,Turnover_{it} + \beta_3 Cash/Assets_{it} + \beta_4 Ever\,Default\,Before_{it}$$
$$+\beta_5 Age_{it} + \beta_6 Age_{it}^2 + \beta_7 ln(Assets_{it}) + \sum_{j=1}^{7} D_j^{Score} \mathbf{1}\{Credit\,Score_{it} = j\}$$
$$+\Gamma \mathbf{Z}_{it} + \iota_{ist} + \iota_{ipt} + \iota_{ibt} + \varepsilon_{it} \tag{16}$$

i denotes a firm, b denotes a bank, s denoted industry, t is year. ι_{ist} is a vector of industry by year fixed effect.[117] ι_{ipt} is a vector of province by year fixed effects.ι_{ibt} is a vector of bank by year fixed effects. It is well established that financing of small and medium firms is tied to local credit market conditions, as proximity between borrowers and lenders facilitates information acquisition ([93]; [94]). We use the perimeter of Italian provinces to define the boundaries of local credit markets. Italian provinces are the natural candidates for the definition of local credit markets for small business lending (see [95]). They constitute administrative units comparable to US counties, and their boundaries are used by Bank of Italy as a proxy of local credit markets for regulatory and supervisory purposes. The regression also includes a quadratic polynomial in age, the natural logarithm of assets, dummy variables for each value of credit score (7 values), ROA, Assets Turnover (Revenues/Assets), Cash over assets, and a dummy equal one if we observe any current or past debt obligations in default, restructured, or in the process of being restructured. These covariates are selected to meet two criteria. On the one end, they represent a parsimonious choice that ensures the existence of a common support between the group borrowers and non-borrowers for every year-market combination. On the other hand, they are observable indicators commonly used by Italian banks to assess firms' riskiness and creditworthiness

117. An industry is defined by a 2-digits Nace Rev. 2 industry code. We also experimented with finer industry classifications: we obtained similar coefficients and R^2.

([71]). In fact, as we show in the paper, all strongly correlate with the probability of default and are significant predictors of the variation in interest rates.

It is important to remark that our dataset provides us with the same source of hard information available to banks. As we discussed in Appendix A.1, banks routinely send data requests to the Credit Register in order to obtain information about the global risk position of their customers and of new firms that approach them (See Appendix A.1.1). The Cerved database is also commonly used by banks to acquire information on firms balance sheets.[118] Of course, individual banks might have access to soft information about their clients or potential clients that the econometrician does not observe. As a consequence, we may not have the same information set of each individual bank.

The vector $\mathbf{Z}_{ibt}$ represents a set of relationship-specific covariates - the number of on-going relationships, and length of each lending relationship - and bank leverage. The exact set of variables in $\mathbf{Z}_{ibt}$ depends on the sub-sample of observations for which we are seeking an estimate of the APR on term loans. As discussed in Appendix A.1, there are 4 types of observations for which information on APR on term loans is missing:

- *Group 1* - BORROWERS-NOLOANS. Firms that have outstanding credit lines with banks in the Taxia database, but no outstanding bank loans
- *Group 2* - BORROWERS-NOTAXIA. Borrowers that appear in the Credit Registry, but for which we observe no information on their APR on loan because their lender do not belong to the group of banks that form the Taxia sample, or because credit has been granted but not yet utilized by the firm.

118. In fact, the Cerved company was originally owned by a consortium of the largest Italian banks that created the company in order to assemble a large, shared database with firms balance sheets that can be used for credit evaluation purposes.

- *Group 3* - BORROWERS-NOCR. Borrowers with no outstanding debt obligations that appear in the Credit Registry, but that report positive bank debt on their balance sheet.

- *Group 4* - NON-BORROWERS. Firms that have not outstanding debt obligations (neither in the CR nor in their balance sheet).

The estimation sample is composed of the group of observations for which we have information on the APR on term loans (BORROWERS-LOANS, *Group 0*).

We now discuss the specific vector $\mathbf{Z}_{ibt}$ for each group.

Group 1. – For these observations, beside firm-specific characteristics and geographical location, we can also use information about their length of lending relations, leverage, and identity of lenders. That is: $\mathbf{Z}_{ibt} = \{\text{Leverage}_{it}, \text{ Length Relation}_{ibt}, \text{Number Relations}_{it}\}$, and both fixed effects (ι_{is} and ι_{bpt}) can be used to predict prices.

Group 2. – The pricing equation for this group of firms is similar to the one adopted for Group 1. The only difference is that, for firms borrowing from lenders that do not belong to the Taxia database, we can not estimate the bank-year fixed effect ι_{bt}. Thus, we construct a province-year fixed effect as weighted average of ι_{bt}: $\iota_{\bar{b}t} = \sum_{b \in Taxia} w_{bst} \iota_{bt}$, where $w_{bst} = Credit_{ibt} / \sum_{b \in Taxia} Credit_{ibt}$ is the market share of the banks b calculated among the banks that belong to the TAXIA database.

Group 3 – The pricing equation for this group is similar to Group 2. The difference is that we do not have information on relationship-level variables for these observations because they do not appear in the Credit Registry records. Therefore, the vector $\mathbf{Z}_{ibt} = \{\text{Leverage}_{it}\}$. Like Group 2, we estimate the pricing model including bank-year fixed effects, and then compute their weighted average vector ($\iota_{\bar{b}t}$) that varies across province-years.

Group 4 – Observations belonging to this group do not engage in credit market transactions. For them, we have no information on relationship-specific variables and bank leverage is zero. Thus, we do not include $\mathbf{Z}_{ibt}$ in the pricing equation (16). Moreover, we restrict the estimation sample to newly established credit relations (LENGTH OF RELATION$_{ibt} \leq 1$ year). The focus on new relationships is important because non-borrowers would be new customers for the bank in case they approach them. It also reduces the information gap between what the econometrician knows about the firm and what the bank knows. [162] and [57] follow a similar approach. We exclude the initial year in our dataset (year 1997), because for this observations we cannot distinguish between new and ongoing relationships. Like Group 2, we estimate the pricing model including bank-year fixed effects, and then compute their weighted average vector ($\iota_{\bar{b}t}$) that varies across province-years.

Using the estimated coefficients and fixed effects, we predict the APR on term loans. For firms in Group 2 with outstanding bank loans, the prediction is done at the relationship level. That is, we predict $\hat{r}_{ibt+1}$, and then we compute the firm-year average APR on term loans, as explained in Section **??** of the paper: $\hat{r}_{it+1} = \sum_b w_{bit} \hat{r}_{ibt+1}$, where $w_{ibt} = {}^{Loans_{ibt}}/_{\sum_b Loans_{ibt}}$. A similar procedure is adopted for firms in Group 1 and firms in Group 2 with no outstanding bank loans. The difference is that we use the share of credit lines as a weight for each ongoing relationship ($w_{ibt} = {}^{CredLines_{ibt}}/_{\sum_b CredLines_{ibt}}$). For firms in Group 3 and 4, we have no information on lenders. Thus, we directly predict $\hat{r}_{it+1}$ at the firm-year level. Table A.8 reports estimates of the pricing equations for the four subsample of observations. Figure A.2 compares the distribution of observed and inferred APR.

Finally, we construct an imputed interest rate for all observations in our dataset (including Group 0) using the prediction of the loan pricing equation adopted for Group 4. We report the distribution of the imputed rate in the last raw of Table A.8. We use this rate to conduct a robustness exercise in Section A.9.

Table A.8: Estimates of loan pricing models

Dep Var. r^{Loans}	*Group 1 & Group 2* Coeff.	SE	p-val	*Group 3* Coeff.	SE	p-val	*Group 4* Coeff.	SE	p-val
ASSETS TURNOVER	-0.0335	0.0008	0.000	-0.0262	0.0008	0.000	-0.0458	0.0023	0.000
ROA	1.0734	0.0091	0.000	1.1496	0.0093	0.000	1.2245	0.0281	0.000
CASH FLOWS/ASSETS	-0.9713	0.0104	0.000	-0.9781	0.0106	0.000	-0.8821	0.0320	0.000
AGE	-0.0042	0.0001	0.000	-0.0018	0.0001	0.000	-0.0107	0.0003	0.000
AGE^2	0.0001	0.0000	0.000	0.0001	0.0000	0.000	0.0001	0.000	0.000
LN(ASSETS)	-0.4532	0.0007	0.000	-0.3205	0.0005	0.000	-0.3103	0.0014	0.000
Z-SCORE 1 (VERY GOOD)	-1.2691	0.0070	0.000	-1.4063	0.0071	0.000	-0.9757	0.0212	0.000
2	-1.2700	0.0066	0.000	-1.3771	0.0066	0.000	-0.9850	0.0196	0.000
3	-1.1992	0.0061	0.000	-1.2861	0.0062	0.000	-0.9047	0.0180	0.000
4	-1.0581	0.0056	0.000	-1.1179	0.0057	0.000	-0.7761	0.0162	0.000
5	-0.8512	0.0055	0.000	-0.8828	0.0056	0.000	-0.5829	0.0158	0.000
6	-0.6686	0.0054	0.000	-0.6860	0.0056	0.000	-0.4487	0.0157	0.000
7	-0.4579	0.0053	0.000	-0.4680	0.0054	0.000	-0.2458	0.0151	0.000
8	-0.3501	0.0052	0.000	-0.3838	0.0054	0.000	-0.1920	0.0149	0.000
9 (VERY BAD)	Omitted Category			Omitted Category			Omitted Category		
DEFAULT EVER BEFORE	0.3493	0.0035	0.000	0.3596	0.0036	0.000	0.3980	0.0114	0.000
LEVERAGE	-0.7256	0.0018	0.000	-0.5292	0.0017	0.000	-	-	-
NUMBER RELATIONS	0.0585	0.0002	0.000	-	-	-	-	-	-
LENGTH RELATIONS	-0.0014	0.0002	0.000	-	-	-	-	-	-
Fixed Effects Estimation:									
INDUSTRY X PROVINCE X YEAR (ι_{spt})	Y			Y			Y		
BANK X YEAR (ι_{bt})	Y			Y			Y		
Subsample:	All			All			New Relations		
ADJ. R2	0.4121			0.4079			0.4153		
OBS	7594152			7594152			1064310		
Fixed Effects Prediction:									
INDUSTRY X PROVINCE X YEAR (ι_{spt})	Y			Y			Y		
AVERAGE BANK X YEAR (ι_{bt})	Y (Group 1)								
AVERAGE BANK X YEAR ($\iota_{\bar{b}t}$)	Y (Group 2)			Y			Y		

Figure A.2. Distribution of borrowing rates: Borrowers (observed) versus non-borrowers (inferred)

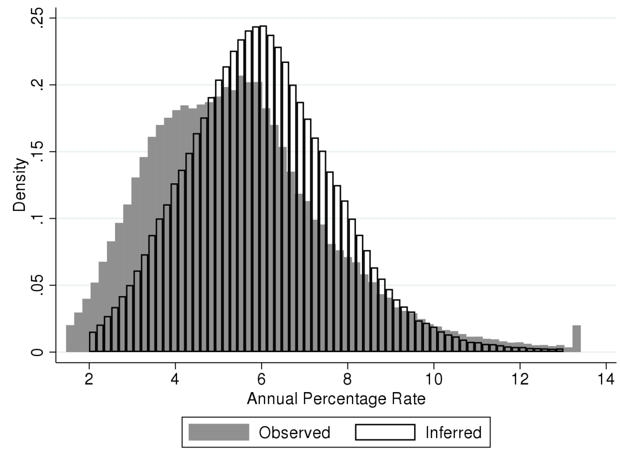


Table A.9: Estimated loan prices

	Mean	Std	p10	p25	p50	p75	p90
BORROWER-LOANS	5.52	2.18	2.99	3.95	5.30	6.67	8.31
BORROWER-NOLOANS	6.25	1.61	4.23	5.08	6.16	7.29	8.39
BORROWER-NOTAXIA	5.67	1.56	3.90	4.67	5.52	6.49	7.56
BORROWER-NOCR	6.71	1.40	5.08	5.79	6.66	7.56	8.33
NON-BORROWER	6.76	1.60	4.85	5.66	6.65	7.73	8.73
ALL IMPUTED	5.75	1.37	4.01	4.74	5.68	6.71	7.58

Robustness – Matching-on-observables raises concerns related to unobserved heterogeneity and to possible selection issues, since soft information might be available to the bank but not to the econometrician and since only transactions for which borrowing/lending is economical for both firms and banks are observed. We perform different tests to analyze our ability to predict interest rates.

First, we look at “crossover firms”. That is those firms who are borrowers in year t but non-borrowers in $t-1$ (type I firms), and those firms who are borrowers in $t-1$ but for which we do not observe outstanding loans in period t (type II firms) . For type I firms we calculate the difference between the observed interest rate in period t and the imputed interest rate in $t-1$; For type II we calculate the difference between the imputed interest rate in period t and the observed interest rate in $t-1$. On average, the difference between observed and estimated rates of these crossover firms is very small: -0.5 percentage points for type I firms and -0.3 percentage points for type II firms.

Second, we perform the following out-of-sample test. Each year, we exclude a random sample of 10% of the firms for which we observe the interest rates, and implement our imputation procedure using the remaining 90% of the observations. We predict the interest rates excluded 10% of the observations using the pricing equation (16) (model used to infer prices for Group 1 and 2). Then, we calculate the difference between the observed interest rate and the imputed one. The difference between observed and imputed rates for the excluded sample is, on average, economically negligible (-0.1 percentage points).

Third, we perform a bounding exercise. Each year, we group firms based on the observable characteristics described above and geographical location. For each group, we take extreme values (5th and 95th percentiles) of the APR observed among observations in Group 0, and attribute these rates to similar firms in Groups 1 - Group 4. This exercise shows that, if firms for which we do not observe the APR on loans were charged a rate among the lowest (highest) paid by similar borrowers, their borrowing costs would be on between 2.4% and 9.6%. Table A.10 shows that these extreme-value imputation procedures have a limited impact on our estimates of gaps and percentage deviation from target capital. In particular, borrowers with outstanding loans still display a significantly lower gap τ^K and percentage deviation ${(K^*-K)}/{K}$ when compared to the other category of firms that either access only lines of credit or do not engage in any type of credit market transaction.

Table A.10: Robustness: Loan pricing with extreme values

Panel a: MRP-cost gap τ^K

		IMPUTATION		
		BASELINE	PC 5	PC 95
BORROWER-LOANS	26.89			
BORROWER-NOLOANS		44.43	47.71	40.87
BORROWER-NOTAXIA		36.79	39.49	32.65
BORROWER-NOCR		41.74	44.99	38.15
NON-BORROWER		60.76	64.19	57.35

Panel b: Deviation from Target Capital ($(K^*-K)/K$)

		IMPUTATION		
		BASELINE	PC 5	PC 95
BORROWER-LOANS	9.19			
BORROWER-NOLOANS		16.67	17.23	12.40
BORROWER-NOTAXIA		14.57	15.02	10.41
BORROWER-NOCR		20.85	21.46	14.37
NON-BORROWER		32.51	33.21	22.20

Finally, we also implement alternative econometric procedures based on propensity score matching used in the literature to solve the problem of unobserved prices ([52]; [57]) and try to correct for sample selection issues using export shifters as an instrument in the selection equation. The estimates of unobserved rates produced by these alternative procedures are similar to the ones produced by our imputation procedure. Regressions are available upon request.

A.3 Theoretical Framework

We consider a firm run to maximizes the present value of cash flows to risk-neutral shareholders, in an environment with endogenous default risk. In each period, the management acting in shareholders' interest decides whether to repay its outstanding debt and continue producing the following period, or rather default on its obligations and transfer ownership and control of the firm to its creditors. If it chooses to repay and produce, the management chooses new factor demands (capital, labor, and intermediate inputs), and how to finance these purchases (bank debt, internally generated cash flow, or capital injection from shareholders). The cost and availability of debt financing depend on the information available to the bank regarding the firm's fundamentals. We consider two alternative scenarios. In one scenario, information is symmetric among firms and banks: competitive lenders provide credit on demand, adjusting the price of credit so that they earn zero-profit in expectations. Borrowers internalize the effect of investment and financing policies on the interest rates, balancing cost and benefits of debt. In a second scenario, banks do not observe firm's productivity and, thus, they have limited information about its default probability. As a result, they offer standardized borrowing contracts to observationally similar firms and impose a borrowing constraint that ties lending to firms net worth in order to break-even in expectation. In both scenarios, when debt is the marginal source of financing, the optimality condition characterizing the capital/debt decision predicts a gap between the marginal revenue product of capital and the user cost of capital (MRP-cost gap). The information embedded the MRP-cost gaps depends on features of the credit contracts. In particular, when interest rates are rigid, the gap is proportional to the shadow cost of capital faced by individual producers. The gap between the marginal revenue product of labor and the wage rate provide information about firms' employment policies. Absent real and government-mandated adjustment costs, firms adjust their workforce to equalize its marginal revenue product to the wage rate paid by the firm. The presence of adjustment costs renders labor demand decisions dynamic, altering the static optimality conditions to include the additional costs incurred by the firm when adjustment takes place.

Production – Time is discrete. Producers - indexed by i - transform inputs into output using production technology

$$Q_{it} = exp^{\tilde{\omega}_{it}+\varepsilon_{it}} F(K_{it}, L_{it}, M_{it}, \gamma) \tag{17}$$

K_{it} is capital, L_{it} is labor, and M_{it} are intermediate inputs (materials and third-party services used in production). γ is a vector of production function parameters. $\tilde{\omega}_{it}$ denotes (log) technical productivity (TFPQ). $F(\cdot)$ is continuous, increasing in all inputs, twice differentiable with respect to its arguments, satisfies the standard Inada conditions, and displays decreasing returns on each individual input ($F_X' > 0$, $F_X'' < 0$ for $X = \{K, L, M\}$). ε_{it} denotes an i.i.d. shock that affects final output, unknown to the firm when period t production decisions are made.[119]

Capital is a quasi-fixed factor of production. Firms own the capital stock. They buy and sell investment goods to adjust their capital stock and replace existing capital as it wears out according to the dynamic constraint

$$K_{it+1} = (1-\delta)K_{it} + I_{it} \tag{18}$$

where δ is the depreciation rate of capital and I_{it} is net investments.

Firms operate in a context of imperfect competition. They face a downward sloping (residual) demand for their products $Q_{it} = P_{it}^{-\eta_{it}}$. P_{it} is the price of firm i final product and η_{it} denotes the price elasticity of demand. Both $\tilde{\omega}$ and η are observed by the firm before

119. ε_{it} represents a non-persistent error that is not observed by the firm when period t production decisions are undertaken. It might represent, for example, expected breakdown, defect, or an ex-post productivity shock.

production decisions. We rule out dynamic pricing behavior, and assume that firms set output prices every period to maximize profits, conditional on the realization of consumers' demand and productivity. In equilibrium firm's charge a markup over marginal costs equal to $\mu_{it} := P_{it}/MC_{it} = (1 + 1/\eta_{it})$. We define revenue (log) productivity (TFPR, as in [78]) as

$$\omega_{it} = \tilde{\omega}_{it} + ln(1 - 1/\eta_{it}) \tag{19}$$

and we assume it evolves following a first-order Markov process whose conditional probability distribution $\Phi(\omega_{it+1}|\omega_{it})$ satisfies the Feller property and is monotone increasing.[120]

Dynamic budget constraint and capital structure – Current period profits might be re-invested into the firm, or distributed to shareholders in the form of dividends. The sources-and-uses of funds equation defines the dividend

$$\hat{D}_{it} = P_{it}Q_{it} - C^K(K_{it}, K_{it+1}) - C^L(L_{it-1}, L_{it}) - P_t^M M_{it} - r_{it}B_{it} + \Delta B_{it+1} \tag{20}$$

$C^K(K_{it}, K_{it+1})$ and $C^L(L_t, L_{t+1})$ denote the total cost of investment and labor:

$$C^K(K_{it}, K_{it+1}) = K_{it+1} - (1-\delta)K_{it} + \psi^K(K_{it}, K_{it+1})$$
$$C^L(L_{it-1}, L_{it}) = w_{it}L_{it} + \psi^L(L_{it-1}, L_{it})$$

where we normalized the price of investment to one and substitute I_{it} using (18), and $\psi^K(K_{it}, K_{it+1})$ and $\psi^L(L_{it-1}, L_{it})$ denote adjustment cost function of capital and labor. w_{it} is the wage rate, which we treat as exogenous (see following discussion). $P_{it}^M M_{it}$ is the total cost of intermediate inputs. On the financing side, firms are protected by limited liability. B_{it} is the debt level maturing in t, $\Delta B_{it+1} = B_{it+1} - B_{it}$ are period t new debt issuances.

120. The model can be easily generalized to allow $\Phi(\omega_{it+1}|\omega_{it})$ to depend on other variables such as export status ([163]) or financial variables ([19]).

Debt is specified with a maturity of one period, but it can be viewed as longer term debt with floating rate. r_{it} is the interest rate paid on debt or earned on savings:

$$r_{it} = \begin{cases} \tilde{r}(K_{it}, B_{it}, \omega_{it-1}) & \text{if} \quad B_{it} > 0 \\ \hat{r} & \text{if} \quad B_{it} \leq 0 \end{cases}$$

$\tilde{r}(K_{it}, B_{it}, \omega_{it-1})$ is the interest rate paid on debt ($B_{it} > 0$), endogenously determined by a risk-neutral competitive lender (see below) in period $t-1$. We allow firms to save ($B_{it} < 0$) by investing in a safe asset that pays a constant, exogenously given rate of return $\hat{r}$. Let $\rho \in (0,1)$ denote the shareholder discount factor between t and $t+1$. We assume $\hat{r} < 1/\rho - 1$ to implicitly capture the tax benefits of debt and limit the scope of precautionary savings.[121]

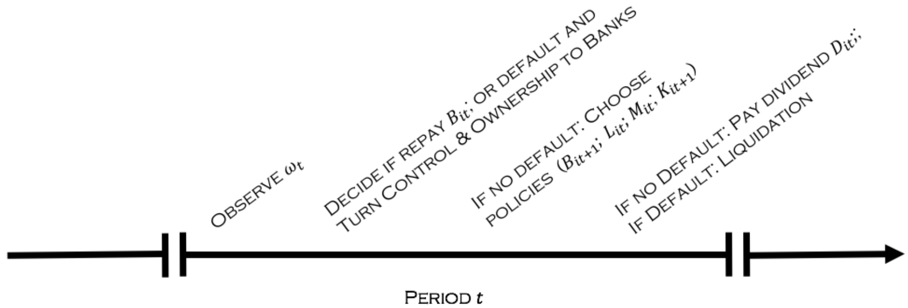
In periods when internal resources are negative but the firm is still valuable as an ongoing concern, shareholders can fill the financing gap - the difference between factor demands and internal funds - issuing negative dividends. In the sprit of [164], we spell out, in a reduced-form fashion, an adjustment cost function for capital injections - $\Psi(\hat{D}_{it}) = \Psi_0 + \Psi_1|\hat{D}_{it}|$, with $\Psi_0 > 0, \Psi_1 > 1$ - and write net distributions to shareholders as[122]

$$D_{it} = \hat{D}_{it} - \Psi(\hat{D}_{it})\mathbf{1}_{\{\hat{D}_{it} < 0\}} \tag{21}$$

121. $1/\rho - 1$ is the pre-tax, risk-free rate of return available to shareholders. The assumption $\hat{r} < 1/\rho - 1$is equivalent to assuming an individual marginal tax rate below the corporate tax rate. Therefore, for a firm that earns positive taxable income, the after-tax return on corporate savings is below the return available to shareholders collecting dividends and investing in their own account. Thus, as the firm cash flow increases, it is easy to show that $-\infty \leq \underline{\mathrm{B}} \leq 0 \leq B_{it}$. If the distribution of TFPR is bounded from above, it is also possible to show that B_{it} is finite. See [77].

122. A similar formulation is often used to model the cost of equity financing for public firms (see [77] and [165]). In our context, where the large majority of firms are privately owned, this reduced-form formulation implicitly accounts for the fact that new capital injections from shareholders might be costly because of asymmetric information fictions in consumer lending markets. Evidently, in the context of the model, it is never optimal to pay positive dividends while raising new finance from shareholders.

Figure A.3. Model timeline



Costly equity issuances break the Modigliani-Miller indeterminacy. Without costly injections, there would be no reason to issue risky debt ($B_{it} > 0$), nor do firms have an incentive to hoard cash ($B_{it} > 0$), so the capital structure decision becomes degenerate. Note that high fixed costs ψ_0 discourage firms from issuing equity to finance small capital purchases, effectively making either internal finance or debt the marginal source of finance.

Default decision – After observing the realization of productivity TFPR ω_{it} and considering its leverage (B_{it}), the firm decides whether it wants to repay its debt and keep control of the firm, or default and turn ownership and control of the firm to creditors. Figure A.3 shows the timeline of events. It can be shown that, for sufficiently high debt levels and low realizations of ω_{it}, manager defaults to safeguard shareholders interests ([166]). In particular, default occurs when TFPR falls below $\bar{\omega}$, implicitly defined by $V(K_{it}, B_{it}, L_{it-1}, \bar{\omega}) = 0$.[123]

123. It is easy to straightforward to envision an opportunity cost of shareholders. To the extent that the continuation value is noncontractable, we would have to distinguish between exit with default and exit without default.

If $\omega_{it} > \bar{\omega}$ the firm produces and chooses its control policies. After revenues are collected, the firm pays dividends to shareholders, and defaults or continues to the following period.[124]

In case of default, shareholders get nothing. Instead, we assume the bank takes control of the firm, it and carries on production choosing and L_{it} and M_{it} to maximize the sales conditional on the assets in place (K_{it}), with no extra investment and no further debt ($I_{it} = B_{it+1} = 0$). At the end of the period, the bank collect the profits of the period ($P_{it}Q_{it} - C^L(L_{it-1}, L_{it}) - P_t^M M_{it}$), and then liquidates the firm.[125]

Lending contract – We now turn to the lending contracting problem. If firms repay their debt obligations, the bank does not verify firms net worth and management retains control. In case of default, banks take control of the firm and extract all bilateral surplus all the non-depreciated firm's assets and cash flows generated by the firm. As in [167], banks can credibly commit to verify firms net worth in the event of default, but verification is costly. We denote by X the percentage of firm assets that are lost in during the bankruptcy process. With this default condition, we assume the interest rate on new debt issuances (r_{it+1}) is pinned down by the zero-profit condition of a representative lender that operates in a perfectly competitive environment.[126] That is, the contractual loan rate is the price

124. As explained above, dividends might be positive (for sufficiently high ω_{it}) or negative if the firm is producing negative cash flows but it still worth more as an ongoing concern.

125. This modeling assumption resembles the automatic stay provisions of the Bankruptcy Code, according to which a firm in default is kept alive - under the supervision of the judiciary - throughout the bankruptcy process. During this time of "normal business activity", the firm borrows no more because no bank would lend to a firm in liquidation. Dividends to shareholders are zero in case of default because banks appropriate all cash flows and assets.

126. If the firm can raise finance by issuing risk-free debt, the only internal solution for debt policy requires $r_{it+1} = \frac{1}{\rho} - 1$, the Modigliani-Miller ([168]) propositions are satisfied, and capital structure would be irrelevant regardless of bankruptcy costs X. Note also that the interest rates are not a function of labor, even in the case when L_{it-1} is a state variable for the firm. This is because, in accordance with absolute priory rules, labor is always paid in full even if the firm subsequently defaults.

that equates the lender's cost of capital ($1/\rho$) to the expected return from lending to risky firms. The interest rate charged by lenders hinges upon their information set at the time of the loan inception. We distinguish between two scenarios characterized either by (1) symmetric information between lenders and firms; or (2) contractual frictions due to banks informational disadvantage.

1. Symmetric information in credit markets. The bank has full information about current productivity ω_{it} and rational expectation about future productivity shocks. That is, lender knows the default states corresponding to each possible $(K_{it+1}, B_{it+1}, \omega_{it})$ triple. In this case,

$$\begin{aligned} &\textstyle\int_0^{\bar{\omega}} ((1-X)(1-\delta)K_{it+1} + Z_{it+1})\, d\Phi(\omega_{it+1}|\omega_{it}) + \\ &((1+\tilde{r}(K_{it+1}, B_{it+1}, \omega_{it}))B_{it+1}) \textstyle\int_{\bar{\omega}}^{\infty} d\Phi(\omega_{it+1}|\omega_{it}) = \frac{1}{\rho} B_{it+1} \end{aligned}$$

where $Z_{it+1} = P(Q_{it+1})Q_{it+1} - C^L(L_{it-1}, L_{it}) - P_t^M M_{it}$ is the revenues generated by the firm during the period.[127] Under perfect information, the firm internalizes the cost of bankruptcy that is passed along via higher interest rates. The required interest rate $\tilde{r}(K_{it+1}, B_{it+1}, \omega_{it})$ is implicitly defined by

$$\tilde{r}(K_{it+1}, B_{it+1}, \omega_{it}) = \frac{\rho - \int_0^{\bar{\omega}} \left(\frac{(1-X)(1-\delta)K_{it+1} + Z_{it+1}}{B_{it+1}}\right) d\Phi(\omega_{it+1}|\omega_{it})}{\int_{\bar{\omega}}^{\infty} d\Phi(\omega_{it+1}|\omega_{it})} - 1 \qquad (22)$$

The interest rate $\tilde{r}(K_{it+1}, B_{it+1}, \omega_{it})$ is increasing in B_{it+1} because higher levels of debt make default more likely and reduce the threshold $\bar{\omega}$. This implies that while lenders do

127. Note that the interest rate demanded by the lender is conditional upon the production and financing policy of the firm. This rules out the debt overhang problem that arises in when managers have discretion over how much to invest and borrow after the terms of the loan have been determined (see [169] and [170]). Note also that, because the stochastic process that governs TFPR is exogenous, the model abstracts from the risk-shifting problem.

not constraint the availability of credit, the presence of default risk endogenously prevents the firm from borrowing an infinite amount, as the interest rate increases with the amount of debt undertaken for any given level of capital. $r(K_{it+1}, B_{it+1}, \omega_{it})$ is also related to K_{it+1} and ω_{it}. Ceteris paribus, higher K_{it+1} implies higher sales, a larger asset base that can be surrendered in default, and a higher threshold $\bar{\omega}$. Highly productive producers are less likely to end up in a state of the world where default is optimal from the firms perspective.

2. *Asymmetric information in credit markets.* As in [11], lenders have imperfect information about the firm. In particular, they are unable to infer the firm-specific probability of default because ω_{it} is unobservable. Instead, they form expectation based on a set of observable characteristics that correlate with the probability of default (such as industry affiliation, age or size), but not necessarily reflects firm-specific productivity. In this context, banks offer loan contracts that consists of a single interest rate for each group ($\bar{r}_{it+1}$), and deal with the diversity by rationing those firms within the group which have a loan demand that exceeds the loan offer ([171]). That is, pooling observationally similar borrowers, banks set the interest rate based on the expected probability of default π_{it+1} (the same for firms "observationally similar" to firm *i*), and cope with default risk imposing a borrowing constraint of the form

$$B_{it+1} \leq \lambda_{it} K_{it+1} \quad \lambda_{it} \geq 0$$

the parameterλ_{it} governs the extent of financial frictions faced by firm *i*. At most a fraction λ_{it} of next period's capital stock can be financed with debt. Or alternatively, the down payment on debt used to finance capital has to be at least a fraction $1-\lambda_{it}$ of the capital stock.[128] Different underlying frictions can give rise to such borrowing constraints; firms' limited commitment ([81]) is an example.

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128. See [38] for a more general formulation of borrowing constraints that depend, for example, on the size of the firm.

When banks offer such a contract, their zero-profit condition for firms similar to firm i is

$$\pi_{t+1}\left((1-X)(1-\delta)K_{it+1}+\bar{Z}_{it+1}\right)+(1-\pi_{t+1})\left((1+\bar{r}_{t+1})\lambda_{it}\bar{K}_{t+1}\right)=\frac{1}{\rho}\lambda_{it}\bar{K}_{t+1} \quad (23)$$

where $\bar{Z}_{t+1}$ and $\bar{K}_{t+1}$ are the expected cash flows and expected demand for capital of firms observationally similar to firm i. The interest rate $\bar{r}_{it+1}$ and the borrowing constraint above are set jointly to satisfy, in expectation, the zero-profit condition of the bank for all firms similar to firm i. Multiple lending contracts, defined by the pair $(\bar{r},\lambda)$, can satisfy the zero-profit condition (23). For example, banks might follow a two-step optimization process. In a first step interest rates are chosen to maximizes expected profits. Then λ_{it} is chosen to satisfy the zero profit condition (23), irrespective of firm-specific productivity, which is unobservable to the bank. This implies that some highly productive firms or firms facing profitable investment opportunities might be willing to pay a higher interest rate to obtain a larger loan, but this would conflict with the purpose the bank and its classification scheme. When borrowing rates do not adjust, credit market frictions such variation in the degree of asymmetric information or in the deadweight loss in case of bankruptcy are passed-through quantity constraints (variation in λ) that generate heterogeneous shadow costs of capital.

Investment and employment policies –The Bellman equation describing the firm's inter-temporal problem is

$$V(K_{it},B_{it},L_{it-1},\omega_{it})=\max_{\substack{L_{it},K_{it+1},\\ M_{it},B_{it+1}}} D_{it}+\rho\int\left[V(K_{it+1},B_{it+1},L_{it},\omega_{it+1})\right]d\Phi(\omega_{it+1}|\omega_{it}) \quad (24)$$

subject to the capital accumulation constraint (18), the dynamic budget constraint (21), and the debt pricing pricing rule.

We heuristically characterize firms' investment policies using the augmented Euler equation of capital. Because new capital injections from shareholder are costly, the firm turns to shareholders financing as a last resort, in response to a rising interest rate on debt or complete rationing from credit markets. This implication of the model is largely consistent with what we find in our data, in which the 99% of firms are not listed in the stock market, and 80% of them borrow from financial institutions to finance their operations. Of the remaining 20% of the observations, 80% finances capital expenditure with some combination of self-financing and trade credit, and less than 5% uses only capital from shareholders, either in the form of debt from shareholders or in-kind contributions. Thus, we restrict our attention to cases when debt is the marginal source of financing for incremental investment. For such firms, the investment optimality condition is characterized by one of the following equations:[129]

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129. In general, equations characterizing the optimal investment and debt policy of the model is characterized by the following equations. Let $\omega_{it} \in [0, \bar{\bar{\omega}}]$, for some arbitrarily large $\bar{\bar{\omega}} > 0$. The optimality condition for debt is

$$\left(1+\mathbf{1}_{\{\hat{D}_{it}<0\}}\Psi_1\right) = \rho \int_{\bar{\omega}}^{\bar{\bar{\omega}}} \left(1+\kappa^B_{it+1}+\psi^K_1(K_{it+1},K_{it+2})\right) d(\omega_{it+1}|\omega_{it}) + \psi^K_2(K_{it},K_{it+1}) \quad (*)$$

where the right-hand side follows from application of Liebnitz's rule and the fact the value of the firm is zero when $\omega_{it+1} = \bar{\omega}$ since we assumed that banks have all bargaining power in case of default. The term κ^B_{it} depends on the model of credit markets. It is equal to $\kappa^B_{it+1} = B_{it+1}\left(\frac{\partial \tilde{r}_{it+1}}{\partial B_{it+1}}\right)$, when borrowers and lenders share the same information about the productivity process. It equals $\kappa^B_{it+1} = \chi_{it}$, when lenders operate with informational disadvantage. $\chi_{it} \geq 0$ is the multiplier on the borrowing constraint. The left-hand size of the equation $(*)$ represents the cost of equity finance. The right-hand side, the discounted shadow cost of an additional dollar of debt.
At an interior optimal financing policy, the investment optimality condition is characterized by

$$\left(1+\mathbf{1}_{\{\hat{D}_{it}<0\}}\Psi_1\right) = \rho \int_{\bar{\omega}}^{\bar{\bar{\omega}}} \left(1+MRP^K_{it+1}-\delta-\kappa^K_{it+1}+\psi^K_1(K_{it+1},K_{it+2})\right) d\Phi(\omega_{it+1}|\omega_{it}) + \psi^K_2(K_{it},K_{it+1}) \quad (**)$$

The right-hand side of equation $(*)$ is the value of a unit of installed capital. Again, the right-hand side of equation $(**)$ follows from application of Liebnitz's rule, and the term κ^K_{it+1} is $\kappa^K_{it+1} = B_{it+1}\left(\frac{\partial \tilde{r}_{it+1}}{\partial K_{it+1}}\right)$, when

$$\rho \int_{\bar{\omega}}^{\infty} \left[MRP_{it+1}^{K} - (\tilde{r}(K_{it+1}, B_{it+1}, \omega_{it}) + \delta)\right] d\Phi(\omega_{it+1}|\omega_{it}) =$$
$$\rho \int_{\bar{\omega}}^{\infty} \left[B_{it+1} \left(\frac{\partial \tilde{r}_{it+1}}{\partial K_{it+1}} + \frac{\partial \tilde{r}_{it+1}}{\partial B_{it+1}}\right)\right] d\Phi(\omega_{it+1}|\omega_{it}) + \tag{25a}$$
$$\psi_2^K(K_{it}, K_{it+1}) + \rho \int_{\bar{\omega}}^{\infty} \psi_1^K(K_{it+1}, K_{it+2}) d\Phi(\omega_{it+1}|\omega_{it})$$

$$\rho \int_{\bar{\omega}}^{\infty} \left[MRP_{it+1}^{K} - (\bar{r}_{t+1} + \delta)\right] d\Phi(\omega_{it+1}|\omega_{it}) =$$
$$\chi_{it}(1 - \lambda_{it}) + \tag{25b}$$
$$\psi_2^K(K_{it}, K_{it+1}) + \rho \int_{\bar{\omega}}^{\infty} \psi_1^K(K_{it+1}, K_{it+2}) d\Phi(\omega_{it+1}|\omega_{it})$$

Equation (25a) characterizes optimal investment policies in the context of symmetric information between banks and firms. The left-hand side represents the marginal benefit of an extra unit of capital, that is the sum of the marginal revenue product of capital ($MRP_t^K = \frac{\partial P_{it} Q_{it}}{\partial K_{it}}$) and the user cost of capital. The right-hand side represents additional costs incurred by the firm when it adjusts its endowment. The first term captures the effect of one extra unit of debt on the interest rate. When banks have full information about the firm, credit is unconstrained and borrowing costs adjust to account for the effect that extra leverage has on the probability of default. The second term accounts for real adjustment costs ([82]). Equation (25b) characterizes the investment policy under asymmetric information. In this case, firms have no control over the interest rate paid on debt, $\left(\frac{\partial \bar{r}_{it+1}}{\partial K_{it+1}} + \frac{\partial \bar{r}_{it+1}}{\partial B_{it+1}}\right) = 0$. Conversely, they may face binding collateral constraints, which result in a shadow cost of capital $\chi_{it}(1 - \lambda_{it})$, where $\chi_{it} \geq 0$ is the multiplier on the borrowing constraint.

The first-order condition with respect to labor, which characterizes optimal employment policies is

borrowers and lenders share the same information about the productivity process, and $\kappa_{it+1}^{K} = -\lambda_{it}\chi_{it}$, when lenders operate with informational disadvantage. When firms use debt as the marginal source of financing, the optimality condition for investment simplify to equation (25a) and (25b).

$$MRP_{it}^{L} - w_{it} = \psi_2^L(L_{it-1}, L_{it}) + \rho \int_{\bar{\omega}}^{\infty} \psi_1^L(L_{it}, L_{it+1}) d\Phi(\omega_{it+1}|\omega_{it}) \tag{26}$$

where $MRP_t^L = \frac{\partial P_{it} Q_{it}}{\partial L_{it}}$ denotes the marginal revenue product of labor. The right-hand side of the equation includes the inter-temporal adjustment costs of labor. Absent adjustment costs, firms flexibly adjusts to their workforce to equalize the marginal revenue product to the wage rate paid by the firm. The presence of adjustment costs renders labor demand decisions dynamic, and alters to static optimality conditions to include the additional costs incurred by the firm when adjustment takes place.[130]

Inflexible Prices and marginal revenue product-User Cost gaps – In the optimality conditions (25a)-(26), the left hand-side of the equation represents the difference between the marginal revenue products of capital and labor and their user costs - $(r_{it+1} + \delta)$ and w_{it}, respectively. Grouping the terms of the right-hand side, we define two random variables (τ^K and τ^L)

$$\begin{aligned} \rho \int_0^{\bar{\omega}} \left[MRP_{it+1}^{K} - (\bar{r}_{t+1} + \delta) \right] d\Phi(\omega_{it+1}|\omega_{it}) = \quad & \chi_{it}(1-\lambda_{it}) + \\ & \psi_2^K(K_{it}, K_{it+1}) + \\ & \rho \int_{\bar{\omega}}^{\infty} \psi_1^K(K_{it+1}, K_{it+2}) d\Phi(\omega_{it+1}|\omega_{it}) \\ & \equiv \tau_{it}^K \end{aligned} \tag{27}$$

$$\begin{aligned} MRP_{it}^{L} - w_{it} = \quad & \psi_2^L(L_{it-1}, L_{it}) + \rho \int_{\bar{\omega}}^{\infty} \psi_1^L(L_{it}, L_{it+1}) d\Phi(\omega_{it+1}|\omega_{it}) \\ & \equiv \tau_{it}^L \end{aligned} \tag{28}$$

130. In case of default at the end of the period, Equation (26) still characterizes optimal labor policies since we assume that firms, now under creditors' control, still produce choosing L_{it} and M_{it} maximizes profits conditional on the state variables of the problem.

In the presence of rigid borrowing costs and wages, distortions in labor and capital accumulation by firms can be empirically measured using firm-level gaps between marginal revenue products and user costs (MRP-cost gaps). From an empirical point of view, this characterization of firm policies is convenient: realized MRP-cost gaps are measurable quantities, when estimates of marginal revenue products and information of user costs are available. Thus, they can be used to cast light on the distribution of the unobservable residuals τ_{it}^{K} and τ_{it}^{L}, and to test the incidence of specific types of frictions and regulations that affect firm policies.

To illustrate this point, consider a labor market regulation that mandates a transfer from firms to workers (a severance payment) when firms layoff workers. For example, consider the following fixed-cost related to downscaling a firms' workforce:

$$\psi^{L}(L_{it-1}, L_{it}) = \left(\mathbf{1}_{[\Delta L_{it}<0]} f^{L}\right) \Delta L_{it} \tag{29}$$

where f^{L} is the size of the per-worker severance payment. Since the classical work of [22], it is well known that, in the absence of contractual and market frictions, the transfer f^{L} can be neutralized by an appropriately designed wage contract: the firm reduces the entry wage of the worker by an amount equal to the expected present value of the future transfer, so as to leave the expected cumulative wage bill arising from the employment relationship unchanged. On the contrary, when wages are inflexible, firms resort to quantity adjustments, which are reflected in the distribution of τ^{L}.[131] This may happen, for example, when wage dynamics are regulated by collectively bargained contracts, as it is the case for Italy like many other European countries. Moreover, when firing costs are size-

131. Note that fixed adjustment costs do not explicitly show up in the first-order condition of the firm during periods of inaction. Yet, the firm's inaction drives a wedge between marginal revenue products and user costs because the firm is not optimizing during inaction periods.

dependent and only born to some firms (for example, only if $L_{it-1} \geq \bar{L}$), the distribution of τ^L is expected to display a discontinuous behavior around the regulatory threshold.

Like labor, MRP-cost gaps for capital are proportional to real rigidities ([172]; [82]; [7]). However, and importantly for our purposes, variation in τ_{it}^K across heterogeneous firms or within firm over time allows us to assess the extent to which investment policies are affected by frictions in credit markets. With flexible interest rates and unconstrained credit supply, interest rates negatively co-vary with productivity to account for the higher likelihood of default, as shown by the pricing equation (22). Contrarily, when banks offer pre-determined interest rates to observationally similar firms, TFPR does not belong to banks pricing kernel, and credit rationing takes place. Moreover, when information frictions are economically relevant, τ^K increases with the degree of information asymmetries between lenders and firms. For firms that are borrowing constrained, $\tau^K > 0$ since the shadow cost of debt $\chi_{it} > 0$, and it is proportional to the degree of asymmetric information frictions faced by each individual firm $(1-\lambda_{it})$. Moreover, as in [11], if credit supply is constrained, a relaxation of information frictions affects quantities (aka marginal products) more than prices (aka interest rates). A second friction embedded in the model is the deadweight cost of bankruptcy $(X(1-\delta)K_{it+1})$ that generates an agency conflict between lenders and borrowers, ultimately reducing lending and depressing investments. The characteristics of the credit contract determine how bankruptcy are costs are passed-on to firms. When interest rates adjust to account for the larger loss given default, higher bankruptcy costs reduce investments because they increase the costs of capital. On the one hand, when the cost of credit is inflexible or only partially adjusts, bankruptcy costs (higher λ) affect investment through quantity constraints, with Corr(X,τ^K)>0.

One consideration that we have not introduced explicitly is corporate and individual income taxes. A direct study of the impact of the tax system on firm policies is beyond the scope of this paper, as it would require detailed information on the incidence of tax exhaustion - which is not in our possess - in order to measure the effective tax parameters facing individual firms. Implicitly, we embedded an assumption about individual versus corporate tax rates in the relation between the discount rate and the return on invested cash shows ($\hat{r} < 1/\rho - 1$) that in order to capture the tax benefits of debt and limit the benefits of precautionary savings. The debt tax shield makes debt finance attractive at low levels of borrowing, and generates a financial "pecking order" ([173]).[132] Finally, a note on the relation between MRP-cost gaps and Tobin's Q. From a theoretical point of view, marginal q - the shadow price of capital - is a sufficient statistic for investment. In particular, under the conditions detailed in [28] and [29], the ratio of equity plus debt value to replacement cost of capital (average q, or Tobin's Q), has been widely uses by the empirical literature as a proxy for the unobservable q and then, to empirically test the impact of financial frictions on investments. More recently, this approximation has been shown to perform poorly in practice (see [174]). Moreover, because it requires some information on firms market value of equity and debt, an empirical measure of Tobin Q is simply not available for private firms. Thus, constructing the optimality condition characterizing optimal investment policies, we have conveniently replaced for q_{it} in the Euler equation characterizing the inter-temporal optimal path of investment with the same term in the first-order condition for investment. This approach is often used by empirical papers who focus on the estimation of empirical Euler equations ([84]; [31]).

132. When debt is the marginal source of financing, both MRP-cost gaps would be multiplied by $(1 - \tau_c)$, where τ_c is the rate of corporate tax. Both the differential treatment of corporate versus personal income and the debt tax shield matters for firms raising funds from shareholders. See [77].

A.4 Production Function Estimation

A.4.1 Estimation Procedure

Our estimation strategy of production function parameters follows the two-stage estimation routine in [9]. The authors prove that restrictions implied by the optimizing behavior of the firm, combined with the idea of using lagged inputs as instruments employed by the dynamic panel and proxy variable literature ([153]; [175]), can identify production function parameters and productivity. With respect to [9], our data allows strengthening the identification procedure of production function parameters using information on borrowing costs to better identify the elasticity with respect to changes in capital. We heuristically describe the estimation steps, referring to [9] for proofs and technical details.

Consider the following production function (in logs):

$$q_{it} = \tilde{\omega}_{it} + f(k_{it}, l_{it}, m_{it}) + \varepsilon_{it} \tag{30}$$

where k, l, m, are the natural logarithm of capital (k), labor (l), and intermediate inputs (m) (material, third-party services, and energy consumption) used by the firm to produce (log) output q; $\tilde{\omega}_{it}$ is firm-level physical productivity (TFPQ) that is observable by the firm when it makes production decisions, but unobserved by the econometrician. ε_{it} represents shocks to production or productivity that are not observable (or predictable) by firms before making their input decisions at t. ε_{it} represents a non-persistent error that is not observed by the firm when period t production decisions are undertaken. It might represent, for example, expected breakdown, defect, or an ex-post productivity shock.

Assumptions

Assumption 1. Productivity – Let $\mathscr{I}_t$ denote firms information set at the beginning of period t, before production choices are made. We assume productivity evolves as a one-period Markov process $\Phi(\cdot)$ that satisfied the Feller property and is monotone increasing. Thus, its probability distribution function distribution can be written as $\phi(\tilde{\omega}_{it}|\{\tilde{\omega}\}_{j=0}^{t-1}) = \phi(\tilde{\omega}_{it}|\mathscr{I}_{it-1}) = \phi(\tilde{\omega}_{it}|\tilde{\omega}_{t-1})$. Thus, we can express $\tilde{\omega}_{it} = \mathbb{E}_t[\omega_{it-1}] + \xi_{it}$, where ξ_{it} is un unanticipated productivity "innovation" such that $\mathbb{E}[\xi_{it}|\mathscr{I}_{it-1}] = 0$, that firms can observe at the moment they make their period t production decisions, but could not anticipate in $t-1$. ε_{it} is a white noise, such that $\mathbb{E}[\varepsilon_{it}|\mathscr{I}_{it}] = \mathbb{E}[\varepsilon_{it}] = 0$ and $\phi(\varepsilon_{it}|\mathscr{I}_{it}) = \phi(\varepsilon_{it})$. Both ω_{it} and ε_{it} are are unobservable to the econometrician.

Assumption 2. Input choices – We distinguish between two types of inputs. (i) *Flexible inputs* (as opposed to *pre-determined*): are inputs that contribute to output in t and are chosen in period t (as opposed to contributing to period t output but being chosen in previous periods). (i) *Dynamic inputs* (as opposed to *static inputs*): previous period levels of dynamic inputs affect period t policies. That is, lagged values of dynamic inputs are period t state variables.

We make the following assumptions. Capital is pre-determined and dynamic: it accumulates according to the accumulation constraint $K_{it} = (1-\delta)K_{it-1} + I_{it-1}$(Equation 18 in the paper), and possibly subject to adjustment costs. Labor is flexible and dynamic: workers are hired in period t after $\tilde{\omega}_{it}$ is observed, they contribute to period t output, but workforce adjustments are possibly subject to adjustment costs. Intermediate inputs are both static and flexible: they are purchases in period t after $\tilde{\omega}_{it}$ is observed, they contribute to period t output, and their price is taken as given by firms.

Assumption 3. Scalar Unobservable and monotonicity – Following [175], we use the inverse-demand for intermediate inputs, to proxy for the unobserved persistent productivity

$\tilde{\omega}_{it}$. We assume that the demand for intermediate inputs can be written as a function of a single unobservable ($\tilde{\omega}_{it}$), and that the input demand for intermediate inputs $\mathbb{M}$ is strictly monotone in $\tilde{\omega}_{it}$.[133] Thus, under Assumption 2, we can express the policy function of intermediate inputs as $m_{it} = \mathbb{M}(k_{it}, l_{it}, \tilde{\omega}_{it})$

Assumption 4. Price taking in intermediate input and output markets – Firms are price takers in the intermediate input and output market, with P_t^M and P_t denoting the common intermediate input price and output prices facing all firms in period t. We discuss the assumption that $P_{it} = P_t$ at the end of this section.

Estimation Routine

The estimation routine consists of two steps. Step 1 non-parametrically identifies revenue elasticities of intermediate inputs and labor using the link between production function and the first order condition of flexible inputs. Step 2 uses the estimates of Step 1 in order to recover the part of the production function that does not depend on intermediate inputs, and to estimates revenue elasticities with respect to capital and labor. We present the exact formulas assuming that $f(\cdot)$ is a second-order Translog

$$\begin{aligned} f(k_{it}, l_{it}, m_{it}; \gamma^M, \gamma) = \quad & \gamma_K k_{it} + \gamma_L l_{it} + \gamma_{KK} k_{it}^2 + \gamma_{LL} l_{it}^2 + \gamma_{KL} k_{it} l_{it} + \\ & \gamma_M^M m_{it} + \gamma_{MM}^M m_{it} + \gamma_{MK}^M m_{it} k_{it} + \gamma_{ML}^M m_{it} l_{it} \end{aligned}$$

It is straightforward to adapt the estimation routine to other functional forms assumptions.

Step 1 – *Recovering the elasticity with respect to intermediate inputs* (θ_{it}^M).

133. See Assumptions 4 and 5 in [99] for further discussion on these assumptions.

The maximization problem with respect to flexible inputs allows us to establish a link between $\mathbb{M}$ and f:

$$\mathbb{M}(K_{it}, L_{it}, M_{it}) = \arg\max_{M_{it}} \mathbb{E}\left[P_t F(K_{it}, L_{it}, M_{it}) e^{\tilde{\omega}_{it}+\varepsilon_{it}} | \mathscr{I}_t\right] - P_t^M M_{it}$$

The FOC with respect to flexible inputs is

$$\frac{P_t^M}{P_t} = \frac{\partial}{\partial M_{it}} F(K_{it}, L_{it}, M_{it}) e^{\tilde{\omega}_{it}} \mathbb{E}\left[e^{\varepsilon_{it}} | \mathscr{I}_t\right]$$

Define $\mathscr{E} \equiv \mathbb{E}[e^{\varepsilon_{it}} | \mathscr{I}_t]$. Use the production function to substitute for $e^{\tilde{\omega}_{it}} = \frac{Q_{it}}{F(K_{it}, L_{it}, M_{it}) e^{\varepsilon_{it}}}$ and obtain

$$\frac{P_t^M}{P_t} = \frac{\partial F(K_{it}, L_{it}, M_{it})}{\partial M_{it}} \frac{1}{e^{\varepsilon_{it}}} \mathscr{E}$$

Then, multiply both sides by M_{it}/Q_{it}, and take logs to obtain the following share equations

$$ln\left(\frac{P_t^M M_{it}}{P_t Q_{it}}\right) = ln\left(\frac{\partial}{\partial M_{it}} F(K_{it}, L_{it}, M_{it})\right) - \varepsilon_{it} + \mathscr{E}$$

Finally, let $s_{it}^M \equiv ln\left(\frac{P_t^M M_{it}}{P_t Q_{it}}\right)$, and taking logs:

$$\begin{aligned} s_{it}^M &= ln\left(\frac{\partial}{\partial m_{it}} f(k_{it}, l_{it}, m_{it})\right) - \varepsilon_{it} + \mathscr{E} \\ &= ln(\theta_{it}^M) - \varepsilon_{it} + \mathscr{E} \\ &= D_M(k_{it}, l_{it}, m_{it}) - \varepsilon_{it} + \mathscr{E} \\ &= D_M^{\mathscr{E}}(k_{it}, l_{it}, m_{it}) - \varepsilon_{it} \end{aligned} \tag{31}$$

We use the share equation (31) to non-parametrically recover elasticity of output with respect to intermediate inputs. To take equation (31) to the data, we need to parametrize the functional $D^{\mathscr{E}}_M(k_{it}, l_{it}, m_{it})$

$$D^{\mathscr{E}}_M(k_{it}, l_{it}, m_{it}) = \sum_{n_K, n_L, n_M} \gamma^{M\mathscr{E}}{}_{r_k, r_l, r_m} k_{it}^{r_k} l_{it}^{r_l} m_{it}^{r_m} \tag{32}$$

for some (n_K, n_L, n_M) that depend on the functional of $f(\cdot)$. In the case of Translog we have

$$D^{\mathscr{E}}_M(k_{it}, l_{it}, m_{it}) = \frac{\partial}{\partial m_{it}} f(k_{it}, l_{it}, m_{it}) = \gamma^{M\mathscr{E}}_M + \gamma^{M\mathscr{E}}_{MK} k_{it} + \gamma^{M\mathscr{E}}_{ML} l_{it} + \frac{\gamma^{M\mathscr{E}}_{MM}}{2} m_{it}$$

It is straightforward to adapt the expressions above to other functional forms.[134] We estimate $\gamma^{M\mathscr{E}}s$ in two steps. First, we estimate$\gamma^{M\mathscr{E}}s$ solving the following minimization problem by non-linear least squares

$$\min_{\gamma^{M\mathscr{E}}} \sum_{i,t} \left\{ s^M_{it} - ln \left(\gamma^{M\mathscr{E}}_M + \gamma^{M\mathscr{E}}_{MK} k_{it} + \gamma^{M\mathscr{E}}_{ML} l_{it} + \frac{\gamma^{M\mathscr{E}}_{MM}}{2} m_{it} \right) \right\}^2$$

We recover an estimate of $\hat{\varepsilon}_{it}$ using the residuals, and an estimate of $\hat{\mathscr{E}}$ taking the average of $e^{\hat{\varepsilon}_{it}}$across all observations. Then, we acknowledge that $\hat{\gamma}^M = \hat{\gamma}^{M\mathscr{E}}/\hat{\mathscr{E}}$, and obtain an estimate of the elasticity θ^M_{it} as[135]

$$\hat{\theta}^M_{it} = \exp\left\{ \hat{\gamma}^M_M + \hat{\gamma}^M_K k_{it} + \hat{\gamma}^M_L l_{it} + \hat{\gamma}^M_{MM} m_{it} \right\}$$

Step 2 – *Recovering the elasticities with respect to capital and labor* (θ^K_{it} and θ^L_{it}).

---

134. We also perform the estimation assuming a different functional form for f. For example, in the case of Cobb-Douglas we have that $D^{\mathscr{E}}_M(k_{it}, l_{it}, m_{it}) = \gamma^{M\mathscr{E}}_0$. [9] propose a semi-parametric sieve estimator (complete polynomial of degree two in all three inputs); in that case, $D^{\mathscr{E}}_M(k_{it}, l_{it}, m_{it}) = \sum_{r_k+r_l+r_m \leq r} \gamma^{M\mathscr{E}}{}_{r_k, r_l, r_m} k_{it}^{r_k} l_{it}^{r_l} m_{it}^{r_m}$.

135. See Theorem 4 in [9].

The second step of the estimation procedure uses the estimates from the first stage of the estimation routine and the recursive nature of the firm's problem in order to recover the elasticities θ_{it}^K and θ_{it}^M. By the fundamental theorem of calculus:

$$\int \frac{\partial}{\partial m_{it}} f(k_{it}, l_{it}, m_{it}) dm_{it} = f(k_{it}, l_{it}, m_{it}) + \mathscr{C}(k_{it}, l_{it}) \tag{33}$$

where $f(k_{it}, l_{it}, m_{it})$ is defined in (30). $\mathscr{C}(k_{it}, l_{it})$ is a constant of integration, function only of capital and labor, to be recovered. We re-arrange the log production function in (30) to express $f(k_{it}, l_{it}, m_{it}) = q_{it} - \tilde{\omega}_{it} - \varepsilon_{it}$, and substitute into (33):

$$\int \frac{\partial}{\partial m_{it}} f(k_{it}, l_{it}, m_{it}) dm_{it} = q_{it} - \tilde{\omega}_{it} - \varepsilon_{it} - \mathscr{C}(k_{it}, l_{it})$$

then, re-arrange the equation above and define the random variable $\mathscr{Y}_{it}$

$$\mathscr{Y}_{it} \equiv q_{it} - \varepsilon_{it} - \int \frac{\partial}{\partial m_{it}} f(k_{it}, l_{it}, m_{it}) dm_{it} = \tilde{\omega}_{it} - \mathscr{C}(k_{it}, l_{it}) \tag{34}$$

Note that, once an estimate of $\theta_{it}^M = \frac{\partial}{\partial m_{it}} f(k_{it}, l_{it}, m_{it})$ and ε_{it} is obtained in first stage of the routine, all quantities in $\mathscr{Y}_{it}$ are "observable" to the econometrician. The random variable $\mathscr{Y}_{it}$ is going to be the base for the estimation of θ_{it}^K, θ_{it}^L, and $\tilde{\omega}_{it}$. Two more steps are needed in order to fully identify rest of the production function. First, we need an estimate of the integrals $\int \frac{\partial}{\partial m_{it}} f(k_{it}, l_{it}, m_{it}) dm_{it}$ $\int \frac{\partial}{\partial l_{it}} f(k_{it}, l_{it}, m_{it}) dl_{it}$; second, we need an estimate of $\mathscr{C}(k_{it}, l_{it})$. Under general polynomial approximations of f, [9] shows that the $\int \frac{\partial}{\partial m_{it}} f(k_{it}, l_{it}, m_{it}) dm_{it}$ has a closed-form solution. In the case of Tranlog:

$$\mathscr{D}_M(k_{it}, l_{it}, m_{it}) = \int D_M(k_{it}, l_{it}, m_{it}) dm_{it} = (\gamma_M^{M\mathscr{E}} + \gamma_{MK}^{M\mathscr{E}} k_{it} + \gamma_{ML}^{M\mathscr{E}} l_{it} + \frac{\gamma_{MM}^{M\mathscr{E}}}{2} m_{it}) m_{it} \tag{35}$$

With information on q_{it} an estimate of ε_{it} and $\mathscr{D}_M(k_{it}, l_{it}, m_{it})$ in hand, we can form a sample analogue of $\mathscr{Y}_{it}$

$$\mathscr{Y}_{it} = q_{it} - \varepsilon_{it} - \mathscr{D}_M(k_{it}, l_{it}, m_{it})$$

Following dynamic panel literature ([153]; [99]), we exploit the Markovian property of $\tilde{\omega}_{it}$ and the dynamic structure of the problem to recover the constant of integration $\mathscr{C}(k_{it}, l_{it})$ and produce estimates of θ_{it}^K, θ_{it}^L , and $\tilde{\omega}_{it}$. Using Assumption 1 and using equation (34) we can write

$$\begin{aligned} \tilde{\omega}_{it} &= h(\tilde{\omega}_{it-1}) + \xi_{it} \\ &= h(\mathscr{Y}_{it-1} + \mathscr{C}(k_{it-1}, l_{it-1})) + \xi_{it} \end{aligned}$$

then, exploiting the recursive properties of the firm's problem and (34), we can express $\mathscr{Y}_{it}$ as a function of current and previous-period capital and labor choices and the innovation ξ_{it}

$$\mathscr{Y}_{it} = \underbrace{h(\mathscr{Y}_{it-1} + \mathscr{C}(k_{it-1}, l_{it-1}))}_{h(\tilde{\omega}_{it-1})} + \mathscr{C}(k_{it}, l_{it}) + \xi_{it}$$

The parametrization of $\mathscr{C}(\cdot)$ depends on the functional for f. In the case of Translog:

$$\mathscr{C}(k_{it}, l_{it}) = \gamma_K k_{it} + \gamma_L l_{it} + \gamma_{KL} k_{it} l_{it} + \gamma_{KK} k_{it}^2 + \gamma_{LL} l_{it}^2 \tag{36}$$

We parametrize $h(\cdot)$ using a second-order complete polynomial series estimator

$$h(\omega_{it-1}) = \sum_{0<a\leq 2} \psi_a \tilde{\omega}_{it-1}^a \tag{37}$$

Since a constant in the production function cannot be separately identified from mean productivity, $\mathbb{E}[\tilde{\omega}_{it}]$, we normalize $\mathscr{C}(k_{it}, l_{it})$ to contain no constant. Combining (36) and (37), we construct following the recursive estimation equation

$$\mathscr{Y}_{it}(\psi,\gamma) = -\mathscr{C}(k_{it}, l_{it}, \gamma) + \sum_{0<a\leq 2} \psi_a \left(\mathscr{Y}_{it-1}(\psi,\gamma) + \mathscr{C}(k_{it-1}, l_{it-1}, \gamma)\right)^a + \xi_{it} \tag{38}$$

and identify the vector of parameters of interest (γs) from the following moment conditions[136]

$$\mathbb{E}[\xi_{it} \cdot z_{it}^{r^k} v_{it}^{r^l}] = 0$$

where z_{it} and v_{it} instruments for k_{it} and l_{it}, respectively. We discuss the set of instruments in the following section.

With estimates of $\hat{\gamma}^M s$ and $\hat{\gamma}$s, we obtain non-parametric estimates of θ_{it}^K, θ_{it}^M of the realization of productivity

$$\hat{\theta}_{it}^K = \frac{\partial \hat{\mathscr{D}}_M(k_{it}, l_{it}, m_{it})}{\partial k_{it}} + \frac{\partial \hat{\mathscr{C}}(k_{it}, l_{it})}{\partial k_{it}}$$

$$\hat{\theta}_{it}^L = \frac{\partial \hat{\mathscr{D}}_M(k_{it}, l_{it}, m_{it})}{\partial l_{it}} + \frac{\partial \hat{\mathscr{C}}(k_{it}, l_{it})}{\partial l_{it}}$$

$$(\hat{\omega}_{it} + \hat{\varepsilon}_{it}) = \hat{\mathscr{Y}}_{it} - \hat{\mathscr{C}}(k_{it}, l_{it}, \hat{\gamma})$$

In the case of Translog:

136. Since $\omega_{it}(\psi) = \hat{\mathscr{Y}}_{it} + \sum_{0<r_k+r_l\leq r} \beta_{r_k,r_l} k_{it}^{r_k} l_{it}^{r_l}$, this is equivalent to regressing ω_{it} on a sieve in ω_{it-1} and - therefore - the moment conditions $\mathbb{E}[\xi_{it} \cdot (z_{it}^{r_k} v_{it}^{r_l})] = 0$ also identify - in a recursive fashion - the ancillary parameters ψs.

$$\hat{\theta}_{it}^{L} = \hat{\gamma}_{ML}^{M} m_{it} + \hat{\gamma}_{L} + 2\hat{\gamma}_{LL} l_{it} + \hat{\gamma}_{KL} k_{it}$$

$$\hat{\theta}_{it}^{K} = \hat{\gamma}_{MK}^{M} m_{it} + \hat{\gamma}_{K} + 2\hat{\gamma}_{KK} k_{it} + \hat{\gamma}_{KL} l_{it}$$

Implementation

Sample – We perform the estimation of production function functions using the longest possible panel dataset available to us, that is the full Cerved database from 1982 to 2013. We perform the production function estimation separately for each 4-digit industry code, to function parameters to allow the structural parameters (γs, βs) to vary across industries.

Variables – Firm-level log output (q_{it}) is log revenues (REVENUES_{it}) deflated with a two-digits output deflator. Labor (l_{it}) is log of effective labor ($\text{WAGE BILL}_{it}/\text{WAGE}_{it}$), deflated using sector CPI. Materials (m_{it}) is log deflated material and services acquired by the firm (MATERIALS_{it}), using industry-level output deflators. Firm's capital (k_{it}) is the series of log deflated fixed assets (both tangible and intangible) calculated with the Perpetual Inventory Method and deflated with the two-digits Nace investments deflator.[137]

Instruments – Because k_{it} is pre-determined, in principle, it can be used as an instrument of itself. Nevertheless, a large literature highlights that, more than any other input in the production process, there are severe errors in the recording the book value of capital stock. This typically leads to downward biased estimates of θ^{K}.[138] We take two steps to address this issue. First, we reconstruct the sequence of capital from the investment se-

137. See Appendix A.1.6 for a description of the procedure followed to construct the capital series with the Perpetual Inventory Method.

138. For example, [101] shows that commonly used estimation techniques in the productivity literature may fail in the presence of plausible amounts of measurement error in the production services provided by capital.

ries following the Perpetual Inventory Method (Appendix A.1.6). Second, we use lagged real borrowing rates ($\tilde{r}_{it-1}$) to construct additional moments conditions to identify γs in equation (38).[139]

We assume labor is a flexible but dynamic input. Thus, we instrument l_{it} using one period lags (l_{it-1}). Lagged values are valid instruments for current labor due to the severe adjustment costs in employment that Italian firms face. As we show in the paper, the provisions of the Italian labor protection law discourage from fully adjusting their workforce in response to TFPR shocks. Moreover, in order for lagged inputs to be a valid instrument for current inputs, input prices need to be correlated over time. We have checked this condition and found an autocorrelation of annual wages of 94%. This, once again, is consistent with the rigidity of wages in Italy, which we document in the paper.

Price-taking in output markets and missing output prices – Unfortunately we do not observe output prices. Thus, we follow the standard practice in the literature, and use deflated revenues instead of physical output (see Assumption 4) ([105]). This is obviously a strong assumption, which is contradicted by the markup estimation of the next section. The implications are that our estimates are potentially subject to the omitted price variable bias discussed in [108], and our estimates of productivity are a proxy of revenue productivity (TFPR). Not controlling for firm-specific output prices would be particularly problematic if estimating productivity was the ultimate goal of this paper ([78]), but it is less of a concern since the relevant productivity variable for our purposes is TFPR (not TPFQ).[140] We must

139. [100] and [145] are prominent examples of papers using variation in input prices to identify production function parameters. See also [101] propose a hybrid IV-Control function approach that instruments capital with lagged investment to attenuate measurement error.

140. The measurement error in output is given by the log ratio of the plant's output price to average industry price, and the dependent variable becomes

$$\ln\left(\frac{P_{it}}{P_{st}}Q_{it}\right) = \ln Q_{it} + \ln(P_{it} - P_{st})$$

also recognize that our data does not allow to draw a distinction between single and multi-product firms. If firms operate across multiple industries or produce differentiated goods, our estimates might be biased because the estimation routine implicitly assumes a single production function and a single consumer's demand curve faced by each firm (see [109] and [105]).

A.4.2 Alternative Estimates of Production Function Parameters

Table A.11 presents estimates of production function parameters obtained using alternative assumptions about the functional form and alternative estimation procedures. In panel a, we present the estimates for the whole sample. In panel b, we split by manufacturing versus non-manufacturing. In every table, the last line reports the share of observations that have at least one negative elasticity estimated to be negative.

Column (1) reports the estimates of Table 1.3, our preferred functional form and estimation procedure. Column (2) and (3) present the estimates using the estimation procedure in [150], but assuming a Cobb-Douglas and a non-parametric functional form, respectively. Functional forms like Cobb-Douglas have proven to be a fairly accurate approximation of production technologies of manufacturing firms. It might not perform equally well in other sectors of the economy. Our results provide evidence in this direction. We show that adopting flexible functional forms as opposed to a more standard Cobb-Douglas is key if one wants to model production technologies of non-manufacturing firms. With respect to our

This price error enters into the estimate of the technical efficiency residual and can lead to bias in both the average level of growth arising from technical efficiency and its volatility. If the price error is correlated with input levels it can also bias the production function estimates, which in turn would lead to another measurement error term in the estimate of technical efficiency. For example, [108] point out that a negative correlation between this price error and input choices arises if plants face downward-sloping demands. In this case, returns to scale would be underestimated and the technical efficiency term would tend to be overestimated. See [176] and [78] for examples of papers where researchers observe both output price and physical output separately.

Table A.11: Alternative production function estimation

Panel a: Whole sample

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	CD	NP	Cost Shares	OLS	No r
θ^K	0.04	0.04	0.05	0.03	0.02	0.04
θ^L	0.29	0.36	0.29	0.21	0.22	0.29
θ^M	0.67	0.63	0.67	0.72	0.77	0.67
RS	1.01	1.03	1.01	0.95	1.01	1.01
Negatives		0.35	0.07	0.00	0.06	0.02

Panel b: Manufacturing VS non-manufacturing

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(8)	(10)	(11)	(12)
	MANUFACTURING						NON-MANUFACTURING					
	Baseline	CD	NP	Cost Shares	OLS	No r	Baseline	CD	NP	Cost Shares	OLS	No r
θ^K	0.05	0.04	0.05	0.04	0.01	0.05	0.04	0.05	0.04	0.03	0.02	0.04
θ^L	0.30	0.35	0.30	0.21	0.24	0.30	0.29	0.37	0.28	0.20	0.21	0.29
θ^M	0.67	0.64	0.66	0.71	0.76	0.67	0.68	0.61	0.68	0.72	0.78	0.67
RS	1.02	1.04	1.02	0.95	1.01	1.01	1.01	1.03	1.00	0.95	1.01	1.01
Negatives		0.21	0.05	0.00	0.11	0.02		0.42	0.09	0.00	0.04	0.02

baseline estimates, assuming a Cobb-Douglas returns negative estimates of at least one elasticity for 42% of the observations referring to firms that operate in the services and construction industries. We also experiment with the semi-parametric sieve estimator proposed by [9]. It is reassuring that this flexible estimator produces estimates θs very similar to one under Translog, and insignificantly different in most industries. Despite the appeal of the semi-parametric sieve estimator in [9], we stick to the Translog functional form as it represents a flexible functional commonly used in the literature. Finally, we compare our baseline estimates to the ones obtained from a similar model where we do not rely on variation in borrowing costs to better identify the elasticity with respect to capital services.

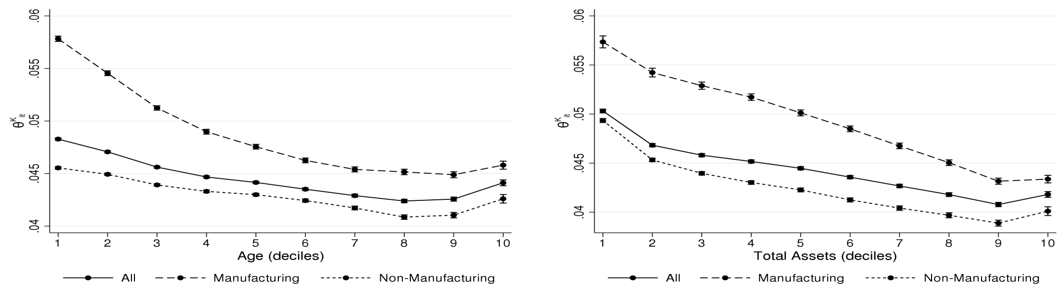
Column (4) reports estimates of elasticities using cost shares (median cost share for each 4-digit industry). As a sanity check, it is useful to compare the technology coefficients with the corresponding revenue costs shares. Cost shares yield factor elasticities under the assumptions of cost minimization and full adjustment of factors ([107]).[141] Based on data on labor compensation we know that in the typical firm around 3% of income share accrues to capital, 21% to labor, and 72% to intermediate inputs and services purchased by the firm (see Table A.11 in Appendix A.4). It is reassuring that our estimates fall in the same ballpark.

Column (5) reports the OLS estimates. A comparison of baseline estimates with the ones obtained via linear least squares provides evidence of the simultaneity bias. OLS estimates of capital coefficients are two times lower and close to zero. Instead, the elasticity with respect to intermediate inputs is upward biased, that picking up variation due to unobserved productivity. Column (6) re-estimates the baseline specification without using

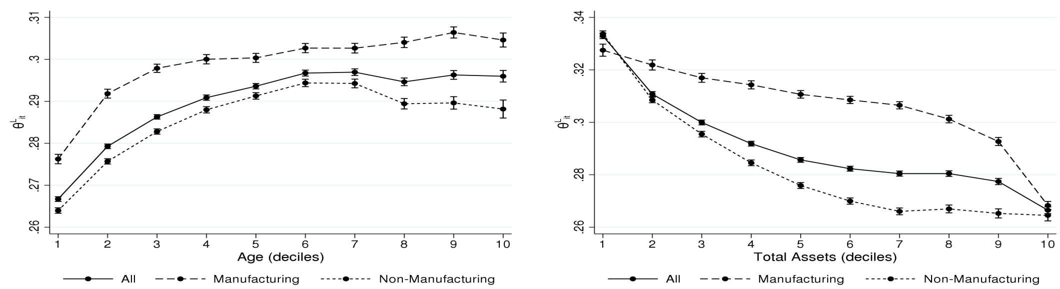
141. The cost-shares approach is another alternative to address the simultaneity problem (see for example [177]). The cost share approach is simple to implement and requires a minimum amount of data. The cost-share approach, however, is not valid in the presence of adjustments costs and it fails to capture large heterogeneity in firms production technologies that characterized the distribution of firms in an industry or changes in over firms lifecycle.

Figure A.4. Output elasticities by age and size

Panel a: Capital Elasticity (θ_{it}^{K})



Panel b: Labor Elasticity (θ_{it}^{L})



lagged borrowing costs to construct an additional moment restriction in the second stage of the estimation. In line with our expectations, we obtain lower estimates of the coefficient θ^{K}, without affecting the elasticity with respect to labor. This suggests that using variation in borrowing prices reduces the attenuation bias driven by measurement error in the capital series.

A.4.3 Output Elasticities by Age and Size

Figure A.4 presents the average output elasticity of capital (θ_{it}^{K}) and labor (θ_{it}^{L}) across the distribution of age and size (deciles).

A.5 Firm Policies, Output Elasticities, and Productivity Shocks

The observed heterogeneity in output elasticities is economically important. Output elasticities affect the curvature of the revenue function and mediate the impact of productivity shocks on firm's policies. This theoretical prediction is evident in the data. We compute a proxy of firm-level TFP ($\hat{\omega}_{it}$) as a residual of the production function estimation, and measure the change in productivity as the difference between the estimated TFPR between the $t-1$ and t ($\Delta\hat{\omega}_{it}$). Table A.12 shows the response of investments to change in productivity ($\Delta\omega_{it}$), and how this response varies as a function of firm's output elasticities. We find a strong and significant response of both investments and labor demand to changes in productivity (Column 1 and 3). A one-percent increase in TFPR leads, on average, to an increase of investments of 38 thousand Euros and of 4 employees. Moreover, in line with the prediction of economic theory, the effect is more pronounced for firms with higher output elasticities of capital and labor (Column 2 and 4). These results are remarkably stable if we focus only on within-firm variation (Columns 5-8), suggesting time-invariant unobservable heterogeneity across firms or measurement error is unlikely to explain these patterns.

Table A.12: Firm policies, output elasticities, and productivity shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δ Investment		Δ Employment		Δ Investment		Δ Employment	
$\Delta\omega$	38.19	28.92	1.28	-0.18	35.50	-1.04	0.97	-2.82
	(1.19)	(2.64)	(0.04)	(0.09)	(2.30)	(4.80)	(0.06)	(0.16)
θ^K		59.92				1435.29		
		(5.56)				(32.23)		
$\Delta\omega * \theta^K$		182.48				780.32		
		(45.10)				(88.73)		
θ^L				1.20				4.53
				(0.04)				(0.12)
$\Delta\omega * \theta^L$				4.10				11.02
				(0.29)				(0.52)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	N	N	N	N	Y	Y	Y	Y
Observations	3216290	3216290	3216290	3216290	3215673	3215673	3215673	3215673
R2	0.00	0.00	0.01	0.01	0.04	0.04	0.19	0.19

A.6 Estimation of Markups

To estimate markups we follow the production side approach pioneered by the seminal work of [102] and recently revisited by [10].[142] Conditional on the state variables of the problem, the first-order condition of the cost minimization problem for static, flexible inputs provides us with an expression relating revenue cost shares and output elasticities to markups. Let $\mathscr{L}$ denote the Lagrangian associated to the cost minimization problem of the firm, and let $\zeta_{it} = \frac{\partial \mathscr{L}_{it}}{\partial Q_{it}}$ denote the marginal cost of production, i.e. the partial derivative of the Lagrangian when the target output is $\bar{Q}_{it}$. The first-order condition for intermediate inputs M_{it} is

$$\frac{\partial \mathscr{L}_{it}}{\partial M_{it}} = P_{it}^{M} - \zeta_{it} \frac{\partial Q_{it}(\cdot)}{\partial M_{it}} = 0$$

Re-arranging terms, we express markups μ - the ratio between output price over marginal cost - as the product of the output elasticity with respect to intermediate inputs and the inverse of the revenue cost share of M in total sales (S_{it}^{M})

$$\underbrace{\frac{P_{it}}{\Phi_{it}}}_{\mu_{it}} = \theta_{it}^{M} \underbrace{\frac{P_{it} Q_{it}}{P_{it}^{M} M_{it}}}_{(S_{it}^{M})^{-1}} \tag{39}$$

The right hand side of (39) is measurable, once estimates of θ_{it}^{M} are available. We follow [10] and correct expenditures shares using the residuals of a regression of inputs on output as a scaling factor.[143] This adjustment helps netting out variation in output not cor-

142. See also [103] for a discussion and application of this methodology.

143. We regress a complete polynomial of order 2 on k_{it}, l_{it}, m_{it} on y_{it}, and compute the corresponding residuals $\approx{e}_{it}$

related with changes in input utilization (such as the one due to demand, inputs prices, or productivity).

$$\hat{\mu}_{it} = \hat{\theta}_{it}^{M} \left(\frac{\frac{P_{it} Q_{it}}{exp(\hat{\varepsilon}_{it})}}{P_{it}^{M} M_{it}} \right)$$

Table 1.3 reports the estimates of markups $\hat{\mu}_{it}$. On average firms price 2% above their marginal cost of production. The right skewness of the distribution drives observed dispersion of markups. Firms located at the 75th and 90th percentile of the distribution price 5% and 15% above marginal cost, respectively.

Empirical validation – We conduct a series of empirical validation of our estimates of markups. First, we correlate our estimates of markups with proxies of firms' profits and intensity of competition (A.13, panel a). We find a strong and positive correlation between markups and firm's profitability (either EBITDA over total assets or ROA). This relationship holds even if we restrict ourselves to within-firm variation. Also, we the administrative boundaries of Italian provinces to define local markets for firms, and for every province-year-industry, we compute the Herfindahl Index (HHI) using revenues shares. Column (9) shows a positive and significant correlation between local product market concentration and markups. Second, our estimates of firm-level markups also display a strong and positive correlation with productivity and with its changes (A.13, panel b), two empirical facts widely documented by the literature (see [10]).[144]

144. For example, in a model of Cournot competition, more productive firms will have a higher market share and hence have higher markups. A positive correlation between productivity and markups is also the prediction of several models with heterogeneous firms and monopolistic competition used in International Trade ([178]).

Table A.13: Markups, Productivity, Profits and Competition

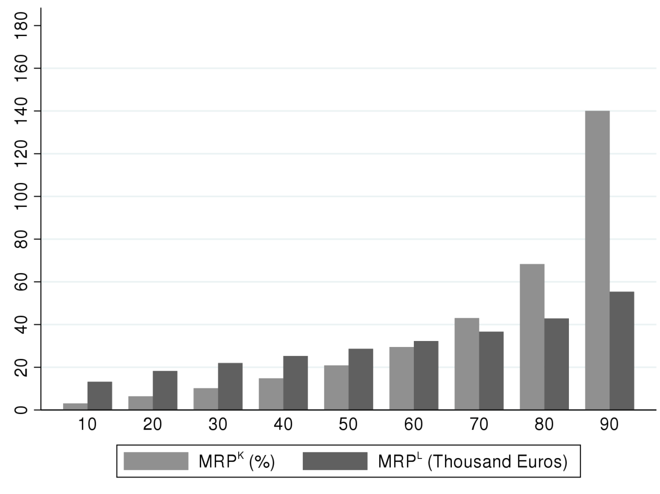
Panel a: Markups and Productivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	MARKUP (μ)							
ω	0.019	0.186	0.186	0.349				
	(0.001)	(0.006)	(0.006)	(0.005)				
$\Delta\omega$					1.057	1.061	1.069	0.994
					(0.003)	(0.003)	(0.003)	(0.003)
YEAR FE	Y	Y	Y	Y	Y	Y	Y	Y
INDUSTRY FE	N	Y	Y	N	N	Y	Y	N
PROVINCE FE	N	N	Y	N	N	N	Y	N
FIRM FE	N	N	N	Y	N	N	N	Y
R2	0.002	0.033	0.035	0.591	0.310	0.335	0.337	0.708
OBSERVATIONS	3923332	3923332	3923332	3815345	3923332	3923332	3923332	3815345

Panel b: Markups, Profits and Competition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	MARKUP (μ)								
$\frac{\text{EBITDA}}{\text{ASSETS}}$	0.480	0.495	0.495	0.480					
	(0.002)	(0.002)	(0.002)	(0.002)					
ROA					0.342	0.353	0.354	0.321	
					(0.002)	(0.002)	(0.002)	(0.002)	
HHI									0.034
									(0.001)
YEAR FE	Y	Y	Y	Y	Y	Y	Y	Y	N
INDUSTRY FE	N	Y	Y	N	N	Y	Y	N	N
PROVINCE FE	N	N	Y	N	N	N	Y	N	N
FIRM FE	N	N	N	Y	N	N	N	Y	N
R2	0.072	0.097	0.098	0.612	0.041	0.066	0.068	0.596	0.002
OBSERVATIONS	3900465	3900465	3900465	3791897	3888003	3888003	3888003	3779013	392264

Figure A.5. Distribution of MRP



A.7 Analysis of marginal revenue products

A.7.1 Distribution of marginal revenue products

This section provides further details on the distribution of marginal revenue products. Figure A.5 displays the asset-weighted distribution of our estimates of the marginal revenue products of capital and labor.

Table A.14 reports summary statistics describing the distribution of the marginal revenue product of capital (MRP_{it}^K) and labor (MRP_{it}^L) split by manufacturing and non-manufacturing, and by borrowers VS non-borrowers. marginal revenue products of capital are expressed in percentage points, while the marginal revenue products of labor expressed in thousand Euros.

A.7.2 Slopes of marginal revenue products

Table A.15 reports the summary statistics of the distribution of the estimated slopes of MRP^K and MRP^L schedules (i.e. $\partial MRP^K/\partial K$ and $\partial MRP^L/\partial L$). Panel a presents summary

Table A.14: Marginal revenue products: Manufacturing VS non-manufacturing

	All Industries			Manufacturing			Non Manufacturing		
	Mean	Median	75-25	Mean	Median	75-25	Mean	Median	75-25
All Firms:									
MRP^K	82.6	21.1	48.6	67.0	19.3	37.1	89.4	22.1	54.6
MRP^L	28.0	24.6	18.8	28.7	26.4	16.6	27.7	23.6	19.6
Borrowers:									
MRP^K	47.4	18.1	35.8	40.3	17.7	30.0	51.5	18.5	40.0
MRP^L	30.4	27.1	18.0	30.2	27.8	15.9	30.6	26.7	19.3
Non-Borrowers:									
MRP^K	74.8	25.2	56.3	80.8	26.3	57.9	73.7	24.9	55.9
MRP^L	21.7	17.5	15.5	19.4	16.6	13.7	22.2	17.7	15.9

Table A.15: Slopes of MRP^K and MRP^L schedules

	Mean	p10	p25	Median	p75	p90
Slope MRP^K schedule	-0.13	-0.36	-0.16	-0.05	-0.01	0.00
Slope MRP^L schedule	-8.00	-40.38	-22.53	-9.94	-1.57	12.42

statistics that characterize the unweighted distributions. On average, a change of 1 thousand reduces the marginal revenue product of capital by 0.13 percentage points. A change of 1 unit of effective labor reduces the marginal revenue product of labor by 19 thousand Euros. Panel b presents the summary statistics of the size-weighted (assets-weighted) distribution. As expected, slopes significantly decrease, reflecting the diminishing marginal products of capital and labor.

A.8 Probability of Exit

We estimate expected probability of exit via a Probit model where the left-hand side variable is an indicator function equal one when we observe the firm exiting in year $t+1$:[145]

$$Exit_{it+1} = F(\alpha X_{it} + \iota_s + \iota_p) \tag{40}$$

The explanatory variables include a set of industry and province fixed-effects (ι_s and ι_p). And a vector of co-variates, all measured in period t. The vector X_{it}includes the state variables of the firm problem in period $t+1$.[146] Moreover, we step outside the strict confines the model and augment the regression with a batter of variables (measures in $t+1$) that provide us with additional information on the expected probability of exit. These variables include firm age (deciles dummies), a set of dummies for each value of credit score (9 dummies), log investment, and a battery of macro-financial variables: percentage change in revenues in the industry-province, change in exit rate, change in unemployment rate (in the region), index of consumer expectation regarding economic situation of the country (national level), percentage change in per-capital GDP (national level), and four risk factors estimated from Italian stock market data (excess return of the market, small-minus-large, value-minus-growth, momentum; see Fama and French (1993))

145. We also experimented with liner probability models and obtain very similar predictions of $P(Exit_{it+1})$.

146. The variable Ever Default Before is a dummy variable that takes value one if ever failed to repay debt obligations in current or previous period,

$$X_{it} = \left[\begin{array}{c} \left.\begin{array}{c} \text{Log Capital, } \omega\text{, Log Employees,} \\ \text{Borrower, Leverage, Ever Default Before} \end{array}\right\} \text{State Variables} \\ \left.\begin{array}{c} \text{Age, Credit Score} \\ \text{Log Investments} \\ \text{Macro-financial Variables} \end{array}\right\} \text{Outside Model} \end{array} \right]$$

Our estimates of the average, unconditional probability of exit is almost 7.3%, matching the un-conditional exit rate of the firms in our sample (Table A.16).[147]

Table A.16: Probability of exit and firm characteristics

This table illustrates the variation in predicted exit rates across firms with different characteristics. We define the following set of dummy variables: small firms are firms with less than 2 million euros in total assets; Young those with age less than 5 years; High leverage are produces with a ratio of bank debt to total assets greater than 0.75; Firms with low credit rating are those with a value of Altman Z-score of 7 or above; Borrowers are those with any outstanding bank debt; The dummy variable Default equals one if we observe any amount of debt in default is observed in the Credit Registry in year t; High and low productivity firms are those with an estimate of ω in the first and forth decile of the distribution, respectively; Manufacturing and Non-manufacturing firms are classified based on the 4 digit industry codes.

Unconditional Exit Rate		7.35	
Probability of Exit Conditional On Firm Characteristics			
SMALL	MEDIUM-LARGE	HIGH LEVERAGE	LOW LEVERAGE
8.56	3.75	7.64	7.28
YOUNG	MATURE	LOW RATING	HIGH RATING
10.36	5.73	11.65	3.95
BORROWER	NOT BORROWER	DEFAULT	NO DEFAULT
6.40	11.02	35.08	6.99
LOW PRODUCTIVITY		HIGH PRODUCTIVITY	
8.70		8.24	
MANUFACTURING		NON-MANUFACTURING	
5.30		8.25	

147. We estimate the regression model on the sample of observations for which we have information on the co-variates of interest, but before applying the sample selection filters 4–6 described in Appendix A.1.

In line with the guidelines of economic theory, the exit probability is decreasing in firm's size, age, and credit rating, and increasing in leverage. The probability of exit of a small firm (assets below 2M Euros) is 1.5 times as large as the probability of a medium-large firm; younger firm (five years or younger) is twice more likely to exit than mature firms; firms with a low credit rating are more than three times as likely to exit; highly leveraged firms (bank debt to assets over 75%) and firms which have defaulted on their debt obligations are also more likely to exit: two and five times more likely, respectively. No access to bank financing also predicts a higher probability of exit, and we find that industries outside manufacturing are characterized by significantly higher churning.

Table A.17: Interest rates and credit market competition

	(1) r_{t+1}	(2) MRP^K_{t+1}
LENGTH RELATION$_t^{weman}$	-0.022	-1.219
	(0.001)***	(0.082)***
LENGTH RELATION$_t^{weman}$ X MEDIUM HHI	-0.001	-0.005
	(0.001)	(0.001)
LENGTH RELATION$_t^{weman}$ X HIGH HHI	0.015	0.015
	(0.002)***	(0.002)***
TFPR$_t$	0.032	
	(0.012)***	
TFPR$_t$ X MEDIUM HHI	0.019	
	(0.015)	
TFPR$_t$ X HIGH HHI	-0.014	
	(0.022)*	
ASSETS TURNOVER$_t$	0.044	23.495
	(0.003)***	(0.371)***
ROA$_t$	1.288	114.568
	(0.038)***	(4.629)***
CASH FLOWS$_t$/ASSETS$_t$	-0.933	-131.020
	(0.051)***	(7.382)***
LEVERAGE$_t$	-0.566	-8.782
	(0.005)***	(0.418)***
NUMBER RELATIONS$_t$	0.027	-0.496
	(0.001)***	(0.067)***
Fixed Effects:		
AGE AND SIZE AND CREDIT SCORE	Y	Y
INDUSTRY X YEAR X PROVINCE	Y	Y
YEAR	Y	Y
ADJ. R2	0.486	0.114
OBS	1887314	1887314

A.9 Information Friction: Additional Analysis

A.9.1 Credit Market Competition

Table A.17 explores the relationship between borrowing rates and credit market frictions. Regressions are run on the sub-sample of borrowers for which the APR on loans is observed. The regressors are described in the paper (Equation 1.5). Standard errors (in parenthesis) are clustered at the firm-level.

A.9.2 Alternative Proxies of Relationship Lending

Table A.18 replicates the analysis in Table (1.5) using the length of the lending relationships of the most important lender (LENGTH RELATION^{lead}) and the length of longest relationship (LENGTH RELATION^{max}), instead of the quantity-weighted length (LENGTH RELATION^{wmean}). Standard errors (in parenthesis) are clustered at firm-level.

Table A.18: MRP-cost gap of capital and length of lending relationship with main lender and longest relationship

Panel a: Length of lending relationship with main lender

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\lvert\tau_t^K\rvert$		τ_t^K		$\lvert\tau_t^K\rvert$		τ_t^K	
LENGTH RELATION$_t^{lead}$	-0.586	-0.016	-1.336	-0.011	-0.490	-0.124	-0.124	-0.115
	(0.031)***	(0.007)**	(0.030)***	(0.007)	(0.026)***	(0.016)***	(0.023)***	(0.016)***
LENGTH RELATION$_t^{lead}$		-0.591		-0.514		-0.180		-0.150
X UNDERCAPITALIZED$_{t-1}$		(0.054)***		(0.053)***		(0.035)***		(0.035)***
LENGTH RELATION$_t^{lead}$			-0.554	0.067			-0.211	0.115
X TFPR$_t$			(0.082)***	(0.020)***			(0.061)***	(0.033)***
LENGTH RELATION$_t^{lead}$				-1.768				-0.942
X UNDERCAPITALIZED$_{t-1}$ X TFPR$_t$				(0.134)***				(0.087)***
TFPR$_t$	30.737				41.532			
	(0.761)***				(1.289)***			
Fixed Effects:								
AGE AND SIZE AND CRED. SCORE	Y	Y	Y	Y	Poly	Poly	Poly	Poly
PROVINCE CONTROLS	N	N	N	N	N	N	N	N
INDUSTRY X YEAR X PROVINCE	Y	Y	Y	Y	N	N	N	Y
YEAR	N	N	N	N	Y	Y	Y	Y
INDUSTRY X YEAR X M. REGION	N	N	N	N	N	N	N	N
FIRM	N	N	N	N	Y	Y	Y	Y
ADJ. R2	0.093	0.166	0.068	0.166	0.574	0.638	0.623	0.638
OBS	1887314	1633492	1633697	1633492	1846643	1614149	1614591	1614149

Table A.18 (cont'ed): MRP-cost gap of capital and length of lending relationship with main lender and longest relationship

Panel b: Length of lending relationship with longest lender

	(1) $\lvert\tau_t^K\rvert$	(2)	(3) τ_t^K	(4)	(5) $\lvert\tau_t^K\rvert$	(6)	(7) τ_t^K	(8)
LENGTH RELATION$_t^{max}$	-0.869	-0.029	-1.937	-0.023	-0.522	-0.311	-0.289	-0.302
	(0.044)***	(0.009)***	(0.038)***	(0.009)**	(0.051)***	(0.035)***	(0.046)***	(0.035)***
LENGTH RELATION$_t^{max}$		-0.915		-0.821		0.144		0.165
x UNDERCAPITALIZED$_{t-1}$		(0.076)***		(0.076)***		(0.052)***		(0.052)***
LENGTH RELATION$_t^{max}$			-0.860	0.062			-0.123	0.034
x TFPR$_t$			(0.103)***	(0.022)***			(0.096)	(0.037)
LENGTH RELATION$_t^{max}$				-2.302				-0.975
x UNDERCAPITALIZED$_{t-1}$ x TFPR$_t$				(0.143)***				(0.093)***
TFPR$_t$	30.744				41.698			
	(0.761)***				(1.290)***			
Fixed Effects:								
AGE AND SIZE AND CRED. SCORE	Y	Y	Y	Y	Poly	Poly	Poly	Poly
PROVINCE CONTROLS	N	N	N	N	N	N	N	N
INDUSTRY x YEAR x PROVINCE	Y	Y	Y	Y	N	N	N	Y
YEAR	N	N	N	N	Y	Y	Y	Y
INDUSTRY x YEAR x M. REGION	N	N	N	N	N	N	N	N
FIRM	N	N	N	N	Y	Y	Y	Y
ADJ. R2	0.093	0.166	0.071	0.167	0.574	0.638	0.623	0.638
OBS	1887314	1633492	1633697	1633492	1846643	1614149	1614591	1614149

Figure A.6. Distribution of firm-specific credit supply shifters

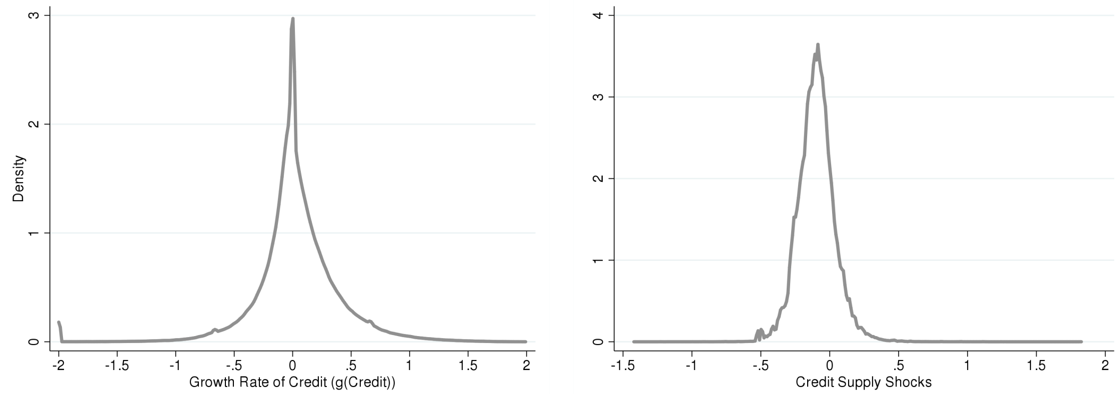


Table A.19: Distribution of firm-specific credit supply shifters

	MEAN	P25	MEDIAN	P75	SD
g(CREDIT)	0.075	-0.094	0.021	0.218	0.329
CREDIT SHIFTER	-0.098	-0.178	-0.098	-0.022	0.127

A.10 Credit Availability: Additional Analysis

A.10.1 Distribution of Firm-specific Credit Supply Shifters

Figure A.6 and Table A.19 display the distribution of the change in bank credit ($g(\text{CREDIT}_{it})$) and of the credit supply shifters ($\text{CREDIT SHIFTER}_{it}$).

A.10.2 Analysis of First Stage Regression

Table A.20 analyzes to what extent the correlation between $g(Credit_{it})$ and Credit Shifter$_{it}$ (i.e., the first stage regression) is affected by the inclusion of a different set of firm-level controls and fixed-effects. We run the following linear model:

$$g(Credit_{it}) = \beta_1 Credit\,Shifter_{it} + \Gamma X_{it-1} + \iota_{spt} + \varepsilon_{it}$$

Table A.20: Analysis of first stage regression

DEP VAR. $g(Credit_{it})$	(1)	(2)	(3) [Baseline]	(4)
CREDIT SHIFTER$_{it}$	0.185	0.180	0.210	0.247
	(0.003)***	(0.003)***	(0.003)***	(0.003)***
FIRM CONTROLS			Y	Y
INDUSTRY X YEAR X PROVINCE FE		Y	Y	
YEAR FE	Y	Y	Y	Y
FIRM FE				Y
ADJ. R2	0.0360	0.0730	0.189	0.307
OBS	1630265	1619183	1610438	1578340

SE (in parenthesis) are clustered at firm-level

In Column (1) we include only year fixed effects. Then, we gradually include a combination of year by industry by province fixed effects (Column (2)), firm-level controls (Column (3), our preferred specification), and firm fixed effects (Column (4)). Column (5) replicates the regression in Column (3) but on the estimation sample of the model with firm fixed effects. We find that the coefficient is remarkably stable across Columns (1)–(3). As we discuss below, the coefficient of the first stage regression is unaffected by the definition of industry (1-, 2-, or 4-digits) (see Table A.21). The inclusion of firm fixed effects slightly increases the correlation coefficient.[148]

A.10.3 Granularity of Industry Effects

Table A.21 analyzes the robustness of the coefficients of the first stage and IV regressions in Table 1.7, to the inclusion of alternative industry fixed effects. Columns (1)–(3) report the baseline coefficients of Table 1.7, which define industry fixed effects using 2-digits indus-

148. The increase in the coefficient from Column (3) to Column (4) does not appear to be driven by the reduction in sample size due to singleton observations in the firm-fixed effect regression. If we estimate the econometric model in Column (3) on the estimation sample of the econometric model in Column (4), we obtain a correlation coefficient of 0.208 (standard error 0.003).

Table A.21: Alternative definition of industry fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	2-DIGIT INDUSTRY FE (BASELINE MODEL)			MACRO-INDUSTRY FE			4-DIGIT INDUSTRY FE		
	FS	ITT	IV	FS	ITT	IV	FS	ITT	IV
	$g(\text{CREDIT}_t)$	$\Delta\tau_t^K$	$\Delta\tau_t^K$	$g(\text{CREDIT}_t)$	$\Delta\tau_t^K$	$\Delta\tau_t^K$	$g(\text{CREDIT}_t)$	$\Delta\tau_t^K$	$\Delta\tau_t^K$
CREDIT SHIFTER$_t$	0.209	-1.801		0.210	-1.659		0.208	-1.849	
	(0.003)***	(0.149)***		(0.003)***	(0.147)***		(0.003)***	(0.162)***	
$g(\text{CREDIT}_t)$			-8.581			-7.898			-8.883
			(0.713)***			(0.696)***			(0.782)***
FIRM CONTROLS	Y	Y	Y	Y	Y	Y	Y	Y	Y
AGE AND SIZE AND CRED. SCORE FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
INDUSTRY X YEAR X PROVINCE FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
ADJ. R2	0.189	0.053		0.184	0.054		0.189	0.056	
OBS.	1610438	1610438	1610438	1620971	1620971	1620971	1518897	1518897	1518897
Test Equality of Coefficients w.r.t Baseline Model (Z statistic):				0.000	0.679	0.679	-0.471	-0.829	-0.250

Standard errors (in parenthesis) are clustered at firm-level try codes. Columns (4)–(6) replicate the regression using macro-industries fixed effects[149]. Columns (7)–(6) replicate the regression using 2-digits industry codes. The bottom of the table reports the Z-statistics of a test of equality of the coefficients with the corresponding coefficients in the baseline regressions. We fail to reject to the null hypothesis that coefficients are the same in the three econometric models.

A.10.4 *Estimated Firm-year Fixed Effects and Change in Productivity*

Table A.22 tests the robustness of the coefficients of the baseline regression in Table A.21 to the inclusion of additional controls for firms' credit demand, and to the inclusion of the simultaneous change in productivity.

We used Model (1.8) to disentangle credit supply movements from simultaneous changes (b_{bt}) in the idiosyncratic credit demand by individual firms (i_{it}). To the extent higher MRP-cost gaps capture potential investment opportunities available to the firm, we a positive correlation between τ^K_{it-1} and the estimated firm-year fixed effects $\hat{i}_{it}$. In line with this intuition, larger (lagged) capital gaps are associated with a greater demand for credit. Unconditionally, one standard deviation increase in $\hat{i}_{it}$ (0.47) is associated to a τ^K_{it-1} 6.6 percentage points larger (Column (1)). Column (2) shows that the statistical relationship between these two variable holds true even if we include in the regression the same controls used in our baseline regression (Equation (1.7) in the paper).

Secondly, we use $\hat{i}_{it}$ to verify that the estimated credit-supply shocks are in fact orthogonal with respect to firms idiosyncratic credit demand (Table A.22, panel a, Columns (3)–(6)). In Column (3) and (5) we report the coefficient of the baseline regression ITT and

149. Macro-industries: Manufacturing; Construction; Wholesale and Retail Trade; Repair Of Machines; Transportation and Storage; Accommodation and Food Service Activities; Information and Communication; Professional, Scientific and Technical Services;5 Administrative and Support Services; Entertainment and Recreation.

Table A.22: Additional controls for credit demand and changes in productivity

Panel a: Controlling for demand using estimated firm-year fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
			ITT		IV	
	τ^K_{t-1}		$\Delta\tau^K_t$		$\Delta\tau^K_t$	
g(CREDIT$_t$)			1.620	-2.275	-8.854	-7.471
			(0.159)***	(0.251)***	(0.875)***	(0.528)***
DEMAND SHIFTER$_t$ ($\hat{i}_t$)	14.184	4.976		1.519		0.586
	(0.159)***	(0.208)***		(0.039)***		(0.149)***
FIRM CONTROLS	N	Y	Y	Y	Y	Y
AGE AND SIZE AND CRED. SCORE FE	N	Y	Y	Y	Y	Y
INDUSTRY X YEAR X PROVINCE FE	N	Y	Y	Y	Y	Y
ADJ. R2	0.005	0.116	0.065	0.066		
OBS.	1466785	1448547	1448547	1448547	1448547	1448547
Test Equality of Coefficients w.r.t Baseline Model (Z statistic):				1.892		-1.582

Panel b: Controlling for simultaneous change in productivity

	(1)	(2)	(3)	(4)
	ITT		IV	
	$\Delta\tau^K_t$		$\Delta\tau^K_t$	
CREDIT SHIFTER$_t$	-1.801	-1.872		
	(0.149)***	(0.149)***		
g(CREDIT$_t$)			-8.581	-9.906
			(0.713)***	(0.731)***
ΔTFPR$_t$		-10.074		-9.964
		(0.238)***		(0.242)***
FIRM CONTROLS	Y	Y	Y	Y
AGE AND SIZE AND CRED. SCORE FE	Y	Y	Y	Y
INDUSTRY X YEAR X PROVINCE FE	Y	Y	Y	Y
ADJ. R2	0.055	0.056		
OBS.	1610438	1610438	1610438	1610438
Test Equality of Coefficients w.r.t Baseline Model (Z statistic):		0.321		-0.312

Standard errors (in parenthesis) are clustered at firm-level

IV regressions (Table A.21 (panel b), Column (1)). Because we can estimate $\hat{\imath}_{it}$ only for firms with multiple lending relationships, the regression includes only this subsample of firms. Then, we augment the model with the firm-year fixed effect (Column (4) and (6)). With a 95% confidence level, we can not reject the null hypothesis that the coefficients of the variable $\text{C}\textsc{redit}\ \text{S}\textsc{hifter}_{it}$ and $g(Credit_{it})$ are the same in the two regressions, as shown by the value of the Z-statistics at the bottom of the table.

Finally, we augment Model (1.8) with the simultaneous change in TFPR (Table A.22, panel b). This control address the possibility that changes in our gaps are driven by an impact of credit on TFPR ([19]) rather than changes in the shadow cost of capital. Columns (1) and (3) report the baseline estimates ITT and IV estimates of Table A.21; Column (2) and Column (4) add the extra control (ΔTFPR_{it}) to the model. With a 99% confidence level, we can not reject the null hypothesis that the coefficients associated to $\text{C}\textsc{redit}\ \text{S}\textsc{hifter}_{it}$ and $g(Credit_{it})$ are the same in the two regressions.

A.10.5 Alternative Firm-specific Credit Supply Shifters

We construct an alternative set of credit supply shifters following the shift-share (Bartik) approach in [17] (GMN, henceforth). Specifically, we estimate - separately for every year t - the following equation that decomposes the contribution of demand and supply factors to banks lending growth:[150]

$$g(Credit_{bpst}) = \mathbf{b}_{bt} + \mathbf{ps}_{pst} + e_{bspt} \quad (\text{weight=}Credit_{bpt})$$

150. In the aggregation of bank loans at the province-sector-year, we exclude the stock of loans in default. To calculate changes in a bank's lending over time without including changes due to acquisitions, we identify acquisitions over every pair of years and treat the acquired and acquiring bank as a single entity over that span (see [128]).

where $g(Credit_{bpst}) = (Credit_{bpst} - Credit_{bpst-1})/(0.5 \cdot (Credit_{bpst} + Credit_{bpst-1}))$ is the normalized growth rate of credit of bank b in province-sector ps, between year t and $t-1$. The vectors $\mathbf{b}_{bt}$ and $\mathbf{ps}_{pst}$ are a vector of bank(-time) and province-sector(-time) fixed effects. The coefficients of interest are the estimated bank fixed-effects. Because province-sector controls are included in the regression, $\mathbf{b}_{bt}$ capture the variation in nation-wide bank-level lending net of the overall change of lending due to province-sector cycles, which purge the bank-specific lending from the effect of local credit demand dynamics. The identification of both $\mathbf{b}_{bt}$ and $\mathbf{ps}_{pst}$ is guaranteed by the presence of multiple banks in each province-sector market (i.e. multiple banks exposed to the same demand) and the presence of each bank in multiple province-sector markets (i.e. multiple markets exposed to the same bank supply conditions). We weight the equation by each bank's period-t lending in province-sector sp so that an observation's influence is proportional to its lending in that year. Then, we construct a firm-specific measure of credit supply shift as

$$Credit\,Shifter_{it} = \sum s_{ibt-1} \hat{\mathbf{b}}_{bt}$$

where $s_{ibt-1} = \frac{Credit_{ibt-1}}{\sum_b Credit_{ibt-1}}$. The set of banks b includes *only* credit institutions that operate on a country-level scale (less than 20% of their total credit volume concentrated in a single province).[151] This distinction is important because Italian credit market is populated by a galaxy of small, local credit institutions. Thus, for this local credit providers, the fixed effects might be imprecisely estimated or it might still capture a local demand component. Note also that weights are constructed using lagged shares of each lender to address possible simultaneity problems. Figure A.7 and Table A.23 show the distribution of Credit Shifter$_{it}$ calculated using the GMN approach: the average and standard deviation are

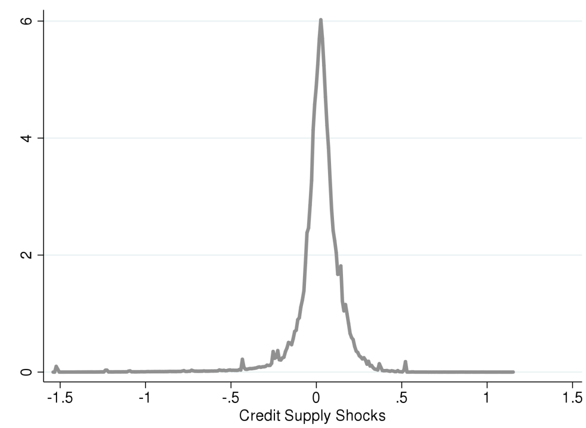
151. We also experiment with alternative thresholds that define national banks (50, 70, 90), and obtain very similar results that are available upon request.

Table A.23: Distribution of firm-specific credit supply shifters: GMN method

	MEAN	P25	MEDIAN	P75	SD
CREDIT SHIFTER	.019	-.023	.026	.079	.012

-1.9% and 12%, respectively. Column (1) of Table 1.7 examines this relationship between

Figure A.7. Distribution of firm-specific credit supply shifters: GMN method



the predicted supply shifter and the growth rate of credit at the firm-level. Comparing two observationally similar firms that operate in the same local credit/product market, but that are exposed to a one standard deviation difference in the credit-supply shock, the firm facing the larger (positive) shock increases its bank debt by 5.6% more (0.473*12). Next, we use the predicted lending shocks to test the effect of changes in credit supply on τ_{it}^{K}. We find that gaps shrink in response to a supply-driven change in the availability of bank finance (Column (2)). All else being equal, one standard deviation difference in credit-supply shock is associated with a reduction of gaps by 0.08 percentage points (-0.699*0.12). Results of the 2SLS model are reported in Column (3). On average, comparing two observationally similar firms whose change in credit supply is one standard deviation apart, the gap of the firm experiencing the larger credit expansion is reduced by 0.5 percentage points more with

Table A.24: Credit supply shifters: GMN method

Column (1) reports the first stage regression; Column (2) reports the Intention To Threat (ITT) regressions, where we project the change in gaps $\Delta\tau_{it}^{K}$ onto the credit shifter; Column (4)-(7) reports the Instrumental Variables (IV) regressions, where we instrument the percentage change in credit supply using the credit supply shifter. All regressions include 2-digit industry by year by province fixed effects and the following set of lagged controls: productivity (TFPR), the weighted average of the length of lending relationships, a second order polynomial in age, log assets, credit score dummies (9 values), assets turnover, ROA, cash flows over assets, leverage, and number of active credit relations. In Columns (5) and (6) regressions also include the interactions of all variables and fixed effects with UNDERCAPITALIZED$_{t-1}$(=1 if $\tau_{it-1}^{K} > 0$), HIGH TFPR$_{t-1}$ (=1 if firm is above median of ω_{it-1}), and UNDERCAPITALIZED$_{t-1}$X HIGH TFPR$_{t-1}$. Regressions are run on the sub-sample of borrowers with outstanding loans for which we observe the APR on loans. Standard errors (in parenthesis) are clustered at the firm level.

	(1)	(2)	(3)	(4)	(6)
	FS	RF		IV	
	g(CREDIT$_t$)	Δt_t^K		Δt_t^K	
g(CREDIT$_t$)			-1.476	0.268	0.031
			(0.321)***	(0.126)**	(0.142)***
CREDIT SHIFTER$_t$	0.473	-0.699			
	(0.003)***	(0.151)***			
g(CREDIT$_t$)				-3.029	-1.935
X UNDERCAPITALIZED$_{t-1}$				(0.580)**	(0.763)
g(CREDIT$_t$)					0.571
X HIGH TFPR$_{t-1}$					(0.234)**
g(CREDIT$_t$)					-2.043
X UNDERCAPITALIZED$_{t-1}$X HIGH TFPR$_{t-1}$					(1.018)**
FIRM CONTROLS	Y	Y	Y	Y	Y
AGE AND SIZE AND CRED. SCORE FE	Y	Y	Y	Y	Y
INDUSTRY X YEAR X PROVINCE FE	Y	Y	Y	Y	Y
ADJ. R2	0.323	0.053			
OBS.	1610438	1610438	1610438	1595056	1595056

respect to the gap of the other firm. The average effect masks the differential impact across firms that, before being exposed to the credit-supply shock, were operating with either an excessive or an insufficient capital endowment (Column (4)). The heterogeneous effect along the productivity margin is also economically relevant (Column (5)).

A.10.6 Case study: the European Sovereign Crisis

In the paper, we study the response of the gapτ^K to changes exogenous changes in credit supply faced by each individual firm. These shifters are agnostic about why banks change their supply of credit. In this section, we examine a specific event that affected banks provision of credit: the 2009-2012 European Sovereign crisis. [48] (BLM henceforth) shows that the Greek sovereign default and the sequence of events that culminated into Greece's bailout request in April 2010 was a "wake- up call" for investors that prompted them to discriminate among different sovereigns based on the quality of their fundamentals, which were largely ignored until then. This change in attitude boosted the volatility of government bond yields in peripheral European countries, including Italy, and widened their spreads vis-a-vis the German Bund. As sovereign securities represent a large fraction of banks' assets, typically the second largest after loans, the shock had a sizable impact on their activity. BLM documents that the negative shock to the sovereign bond market had a negative, causal effect on lending. When they compare lending to the same firm by two banks that are one standard deviation apart in terms of pre-crisis sovereign exposure, we find that the more exposed financial intermediary reduced its credit supply by 10% more relative to the other. The contraction in credit supply caused by the sovereign shock had a sizable effect on firms' ability to access bank financing. They find that the lenders' exposure at the onset of the sovereign crisis is highly predictive of the change in a firm's total bank credit spanning the burst of the sovereign crisis. To one standard deviation increase in lenders' average holdings of Italian sovereign securities before the sovereign shock corresponds to a reduction of 5% in the firm's total bank borrowing, compared with its pre-crisis amount. This suggests that, because of credit-market imperfections, firms were unable to compensate the reduction in credit from more exposed lenders by expanding their borrowing from less exposed financial intermediaries.

Following BLM, we construct a measure of banks' exposure to the sovereign crisis, exploiting variation in firms exposure to banks with differential holdings of sovereigns

$$\text{Sovereign Shock}_{iPRE} = \sum s_{iPRE} \text{Sovereigns}_{bPRE}$$

where $s_{iPRE} = \frac{\text{Credit}_{ibPRE}}{\sum_b \text{Credit}_{ibPRE}}$ is the share of bank b on firm i total credit, measured before the Greek bailout (average exposure between 2009:Q2 and 2010:Q1); Sovereigns_{iPRE} is the exposure of bank b to Italian government bonds at the end of 2010:Q1 scaled by risk-weighted assets, which is a bank-specific measure of financial institutions' exposure to the sovereign shock.

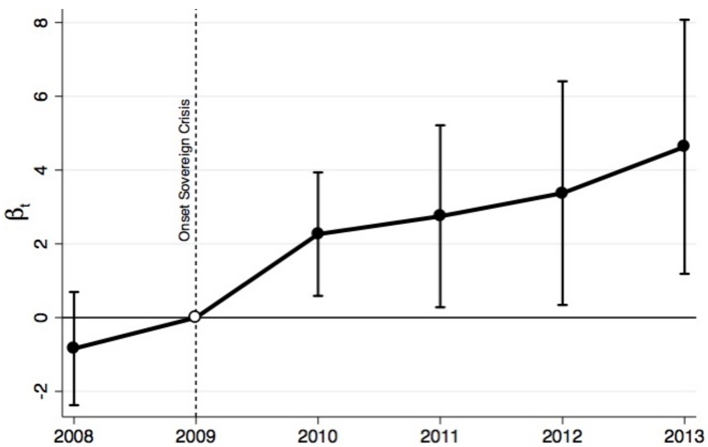
We find that the correlation between the variable $\text{Sovereign Shock}_{iPRE}$ and the 2009-2010 credit supply shifter ($\text{Credit Shifter}_{i2010}$) obtained following the shift-share approach in Section 1.5.1 of the paper are negatively correlated. The raw correlation is 16%. In terms of magnitude, to one standard deviation increase in $\text{Sovereign Shock}_{iPRE}$ we find a reduction of $\text{Credit Shifter}_{i2010}$ by 9% (or 3/5 of a standard deviation of the credit-supply shock). This provides evidence of the external validity of our bank-specific shifters.

Next, we test the impact of the sovereign shock on the change in the capital, estimating the empirical model in BLM:

$$\Delta_t \tau_i^K = \alpha_t + \beta_t \text{Sovereign Shock}_i + \Gamma \cdot X_{iPRE} + \Lambda \cdot Z_{iPRE} + \iota_p + \iota_s + u_i$$

where $\Delta_t \tau_i^K = \tau_{it}^K - \tau_{i2009}^K$ is the change in the gap between year $t \neq 2009$ and the gap in year 2009; X_{iPRE} are a firm-specific weighted average of bank characteristics, and Z_{iPRE} are a set of relationship-specific variables, all measured in 2009; ι_p and ι_s are a battery of province and industry fixed effects, respectively.[152] Figure A.8 reports the estimated coefficients and relative standard errors. On average, following the burst of the sovereign crisis, one standard deviation increase in banks' holdings of Italian sovereign securities (0.23) corresponds to an increase of 0.5 percentage points in τ^Kin the year following the burst of the sovereign crisis.

Figure A.8. The (mis)allocative effects of the European sovereign crisis



To the extent that the change in the gap captures a change in the shadow cost of capital for these firms, it suggests that the real effects of the sovereign crisis are long-lasting. Four years after the burst of the crisis, we find an average cumulative change of 1 percentage point. Importantly, we find no effect of lenders exposure to sovereigns on the change in gaps before the onset of the crisis, which, in line with the findings in BLM, suggests no pre-trending.

152. The econometric model is identical to the one in [48] (equation (2)). Standard errors are clustered at the level of the lead bank, which is the largest lender during the pre-bailout period. We refer to [48] for further details on the regression and sample selection. We also experimented with industry (4 digits) by province fixed effects and obtain very similar results.

Table A.25: MRP-cost gaps of capital and credit-supply shocks

Panel a: OLS, First Stage, and ITT regressions

	(1)	(2)	(3)	(4)	(5)
	OLS	FS		ITT	
	$\Delta\tau_t^K$	$g(\text{CREDIT}_t)$		$\Delta\tau_t^K$	
$g(\text{CREDIT}_t)$	-2.918				
	(0.045)***				
CREDIT SHIFTER$_t$		0.155	0.216	-1.435	-0.959
		(0.003)***	(0.003)***	(0.126)***	(0.137)***
FIRM CONTROLS	Y	Y	Y	Y	Y
INDUSTRY X YEAR X PROVINCE FE	Y	Y	N	Y	N
YEAR FE	N	N	Y	N	Y
FIRM FE	N	N	Y	N	Y
ADJ. R2	0.051	0.093	0.214	0.049	0.123
OBS.	2130457	2130457	2086179	2130457	2086179

Panel b: IV regressions

	(1)	(2)	(3)	(4)	(5)
			$\Delta\tau_t^K$		
$g(\text{CREDIT}_t)$	-9.265	-4.438	-1.034	-6.378	-0.885
	(0.821)***	(0.632)***	(0.301)***	(0.933)***	(0.311)***
$g(\text{CREDIT}_t)$			-9.455		-7.197
x UNDERCAPITALIZED$_{t-1}$			(1.447)***		(1.741)***
$g(\text{CREDIT}_t)$				5.157	-0.417
x HIGH TFPR$_{t-1}$				(1.703)***	(0.547)
$g(\text{CREDIT}_t)$					-3.965
x UNDERCAPITALIZED$_{t-1}$x HIGH TFPR$_{t-1}$					(2.337)*
FIRM CONTROLS	Y	Y	Y	Y	Y
INDUSTRY X YEAR X PROVINCE FE	Y	N	Y	Y	Y
YEAR FE	N	Y	N	N	N
FIRM FE	N	Y	N	N	N
OBS.	2130457	2086179	2115436	2114586	2115436

A.10.7 Analysis on the Full Sample of Borrowers

Table A.25 replicates the regression of Table 1.7 in the paper on the sub-sample of borrowers for which we have information on their lenders, including those for which we infer the APR on loans.[153] See Appendix A.2.2 for details on the procedure used to infer the price of credit. Standard errors (in parenthesis) are clustered at firm-level.

153. This sub-sample includes firms in Group 0, Group 1, Group 2, and Group 3. See Appendix A.2.2.

A.11 Labor Market Frictions: Additional Analysis

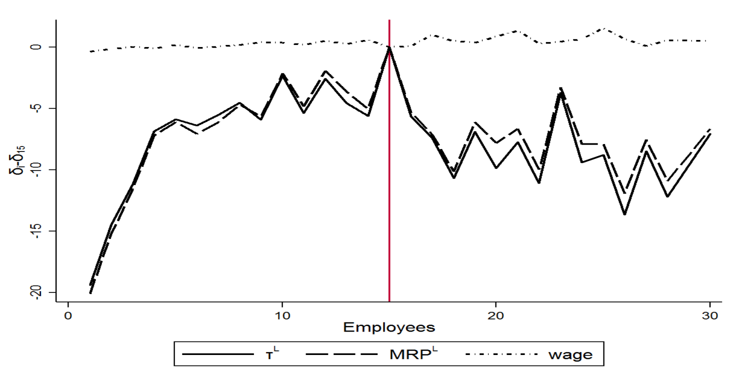
A.11.1 Productivity Shocks

Figure A.9 reports the estimates of δ_k of the following regressions that studies how positive changes in productivity ($\Delta\omega > 0$) impact MRP-cost gaps of labor and its components (wages and MRP^L). More formally, for all firms below 30 employees we estimate the model:

$$y_{it} = \sum_{j=1}^{30} \beta_j D(j)_{it} + \gamma \Delta^+ \omega_{i,t} + \sum_{j=1}^{30} \delta_j D(j)_{it} \Delta\omega_{i,t} + X_{it}\theta + \varepsilon_{it}$$

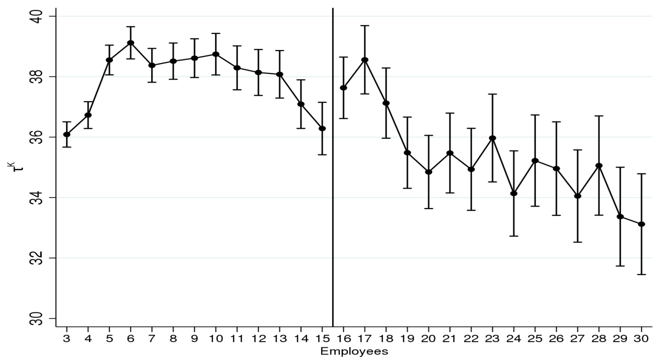
where $y_{it}$is, alternatively, τ^L_{it}, MRP^L_{it}, w_it; $D(j)_{it}$ are a set of dummies equal to 1 if (lagged) size equal j; $\Delta\omega_{i,t}$ is the change in TFP between year $t-1$ and t.

Figure A.9. Response of wages, MRP^L and τ^L to productivity shocks



The vector of controls X include lagged TFP, a quadratic in age, and (alternatively) sector-province-year fixed effects or year and firm fixed effects. The vector δ_k provides estimate of the association between changes in productivity and the dependent variable for different size categories. The coefficients δ_k are reported as deviations from the δ_{15} (the baseline category).

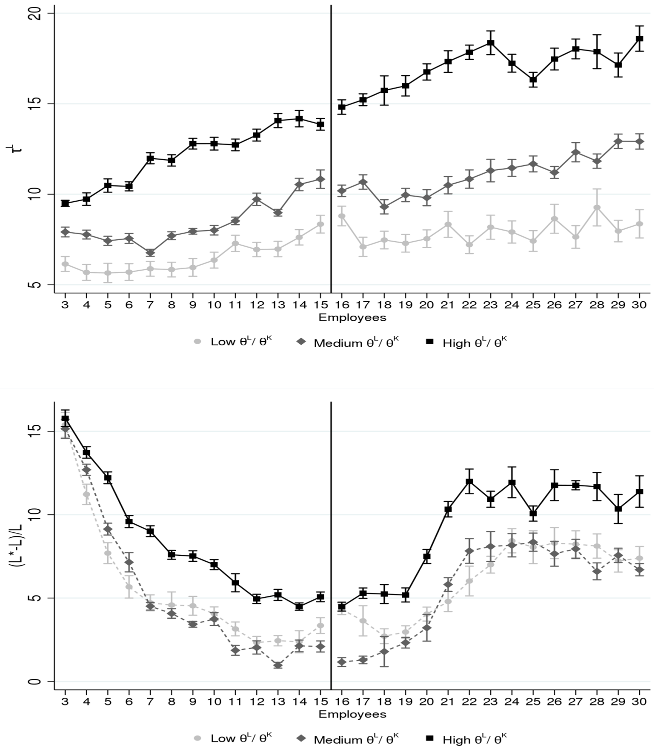
Figure A.10. MRP-cost gaps of capital



A.11.2 Capital-Labor Substitution

FigureA.10 displays the average τ_{it}^{K} across firms with a different number of employees. We are interested in the pattern around the 15-employees threshold. Figure A.11 displays the average τ_{it}^{L} and $(L_{it} - L_{it}^{*})/L_{it}$ across firms with a different number of employees, splitting firms into industries with high, medium, and low labor intensity.

Figure A.11. MRP-cost gaps of labor by labor intensity of production



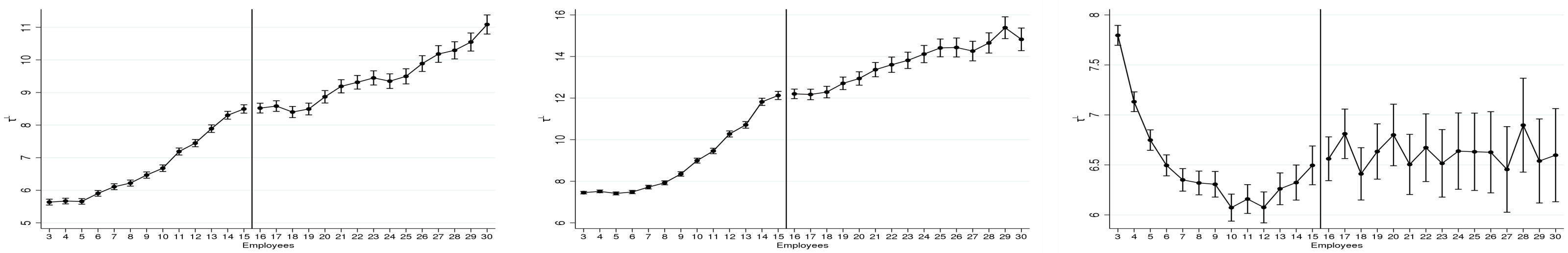
Industries are classified as highly labor intensive when the average ratio $\theta_{it}^{L}/\theta_{it}^{K}$ is above third tercile of the distribution of $\theta_{it}^{L}/\theta_{it}^{K}$ industry ratios. Vice versa, an industry is classified as low or medium labor intensity when the industry $\theta_{it}^{L}/\theta_{it}^{K}$ ratio belongs to the first and second tercile of the distribution, respectively.

A.11.3 Industry Heterogeneity

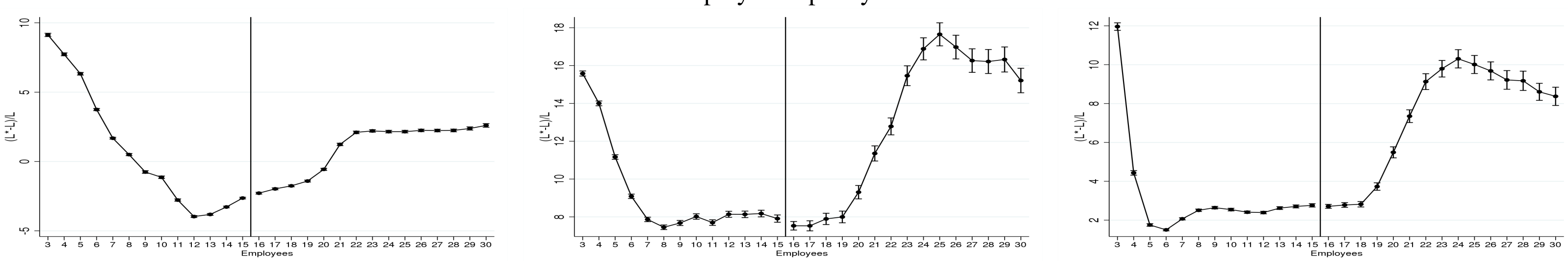
Figure A.12 displays labor gaps (τ_{it}^{L}), percentage deviations from target employment ($(L_{it}^{*} - L_{it})/L_{it}$) of firms with different size.

Figure A.12. Labor market frictions by industry

Panel a: MRP-cost gaps of labor



Panel b: Employment policy distortions



A.12 Aggregate Implications: Additional Analysis

A.12.1 Reallocation Algorithm

We want to study how much aggregate TFP and output would change if it was possible to reallocate capital and labor across firms, without changing the aggregate amount of resources in the economy. To do so, we define the following counterfactual outcome Y_{it}^{**}

$$\begin{aligned} Y_{it}^{**} &= e^{a_{it}} \cdot \left(K_{it}^{**}\right)^{\gamma_s} \left(L_{it}^{**}\right)^{1-\gamma_s} \\ \text{s.t.} \quad L_t^{**} &= \textstyle\sum_i m_{it}^L L_{it}^* = L_t \\ K_t^{**} &= \textstyle\sum_i m_{it}^K K_{it}^* = K_t \end{aligned}$$

for some reallocation weight $m_{it}^L \gtreqless 0$ and $m_{it}^K \gtreqless 0$ that meet the following criteria:

1. $m_{it}^X \geq 0$ when $\tau_{it}^X > 0$.
2. when $a_{jt} \geq a_{it}$: (i) $m_{jt}^X \leq m_{it}^X$ if ($\tau_{jt}^X \leq 0$ & $\tau_{it}^X \geq 0$); (i) $m_{jt}^X \geq m_{it}^X$ otherwise.
3. $\frac{\partial P\{m_{it}^X > 0\}}{\partial \omega_{it}} \geq 0$ if $\tau_{it}^X \geq 0$; $\frac{\partial P\{m_{it}^X < 0\}}{\partial \omega_{it}} \leq 0$ if $\tau_{it}^X < 0$.

The endowments L_{it}^* and K_{it}^*, defined in equations (1.12a) and (1.12b) of the paper represent the amount of target input demands that close the gaps τ_{it}^L and τ_{it}^K at the observed user costs.

As discussed in the paper, the first criterion requires resources to move in a welfare-enhancing direction, from negative MRP-cost gap producers toward positive gap firms. The second condition remarks that the reallocation takes place with no change in the aggregate capital and labor endowment of the economy. The third condition says that reallocation follows a productivity rank.

The following algorithm produces a set of weights m_{it}^L and m_{it}^K that satisfying the criteria above. First, every year, we group firms into positive and negative MRP-cost gaps. Within each group, we rank firms based on the realization of firm-level productivity a_{it}. Then,

Figure A.13. Reallocation algorithm

Firm ID	τ^X	Productivity	ΔX	Aggregate X	Post-reallocation demand
1	+	0.5	2	2	$X^{**} = X^*$
2	+	0.4	7	9	$X^{**} = X^*$
3	+	0.3	5	12	$X^{**} = X^*$
4	+	0.2	4	16	$X^{**} = X$
5	+	0.1	1	17	$X^{**} = X$
				17	
6	-	0.6	5	5	$X^{**} = X^*$
7	-	0.7	2	7	$X^{**} = X^*$
8	-	0.8	4	11	$X^{**} = X^*$
9	-	0.9	1	12	$X^{**} = X^*$
				12	

every year, we start reallocating resources from the firm with lowest TFP among negative-gap producers to the firm with the highest productivity among positive-gap firms. The amount of the transfer is equal to the amount of input $X = \{K, L\}$ that would close the gap of the negative-gap firm. If this transfer is sufficient or exceeds to amount needed to close the gap of the positive MRP-cost gap firm, then the reallocation moves on and the resources in excess are employed to close the gap of the firm second-highest firm among the positive-gap producers. If this transfer is insufficient, the additional resources needed to close the gap of the positive-gap producer are provided by the firm with the second-lowest productivity among the negative MRP-cost gap firms. The reallocation continuous following the productivity ranking as shown in the example of Figure A.13, and it stops when the aggregate constraint binds ($\sum_i X_{it}^{**} = X_t^{**} = X_t = \sum_i X_{it}$, for $X = K, L$). When, in a given year, the amount of resources needed by positive MRP-cost gaps firms exceeds the amount of resources that can be transferred from negative MRP-cost gap firms, it must be the case that, for some positive gaps are not closed. On the contrary, it is possible that the amount of resources needed by positive MRP-cost gaps firms is less than the amount of resources that can be transferred from negative MRP-cost gap firms. In this case, we reallocate the resources in excess freed by negative-gap producers across all firms: each firm gets a share of those resources proportional to the relative productivity.

Using the algorithm above, it is straightforward to impose constraints in the reallocation of resources. For example, we can constraint the reallocation to take place with each industry-year. The only difference is that now the groups of positive and negative-gaps producers and their sorting based on productivity has to be done for each year-industry pair.

A.12.2 Aggregate Endowments and Deviations from Aggregate Target Output

Figure A.14 panel a presents the difference between the two aggregate demands in terms of percentage deviations

$$\begin{aligned}\frac{L_t^*-L_t}{L_t} &= \frac{\sum_i L_{it}^*-\sum_i L_{it}}{\sum_i L_{it}}\\ \frac{K_t^*-K_t}{K_t} &= \frac{\sum_i K_{it}^*-\sum_i K_{it}}{\sum_i K_{it}}\end{aligned}$$

where $K_t = \sum_i K_{it}$ and $L_t = \sum_i L_{it}$ are the aggregate input demands in the economy, and $K_t^* = \sum_i K_{it}^*$ and $L_t^* = \sum_i L_{it}^*$ are the aggregate target input demands. Averaging across years, our calculations suggest the Italian corporate sector as a whole would need to increase its capital endowment by approximately 1.2% and would need to higher approximately 9% more effective units of labor if primary inputs were chosen by individual producers to equalize Marginal Products to user costs.

We calculate the loss in aggregate output aggregating firm-specific deviations from target output

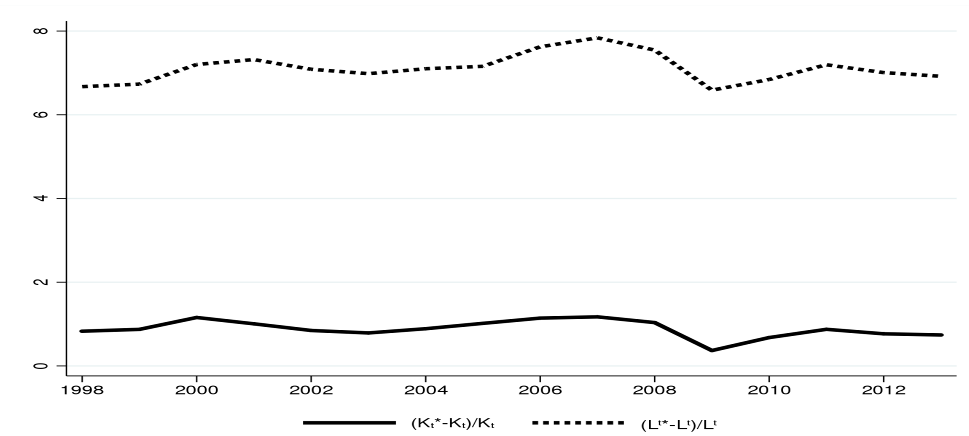
$$\frac{Y_t^* - Y_t}{Y_t} = \frac{\sum_i Y_{it}^* - \sum_i Y_{it}}{\sum_i Y_{it}}$$

where Y_{it} and Y_{it}^* are defined in (1.14) and (1.13). Table A.26 shows that aggregate output would grow, on average, by 8-9% if primary inputs could be frictionlessly allocated to firms in the economy. At an aggregate level, the difference between Y_t^* and Y_t results from the interplaying of two forces. Mechanically, a first force generating $Y_t^* \neq Y_t$ is a difference in aggregate endowments (Figure A.14, panel a). This force reduces output gains during recession times because the drop in aggregate consumer demand reduces the gap between L_t^* and L_t and K_t^* and K_t. This is the case, for example, of the two recession periods that followed the burst of the dot-com bubble and - more remarkably - during the recent

Table A.26: Aggregate implications: output and TFP gains from closing all gaps

	EXTRA AGGREGATE CAPITAL NEEDED	EXTRA AGGREGATE LABOR NEEDED	OUTPUT (TFP) GAIN
1998 - 2001	1.05 %	6.92 %	8.60 %
2002 - 2007	1.06 %	7.23 %	9.02 %
2008 - 2013	0.85 %	6.95 %	9.15 %
AVERAGE	0.99 %	7.03 %	8.93%

Figure A.14. Aggregate resources needed to fully close gaps



financial crisis. Vice versa, this force increases gains in upward phases of the business cycle.

A.12.3 Alternative Measures of Efficiency of Resource Allocation

Figure A.15 (panel a) presents the time-series of the dispersion of log marginal revenue products of capital and labor.

Figure A.15. Alternative aggregate measures of efficiency of resource allocation

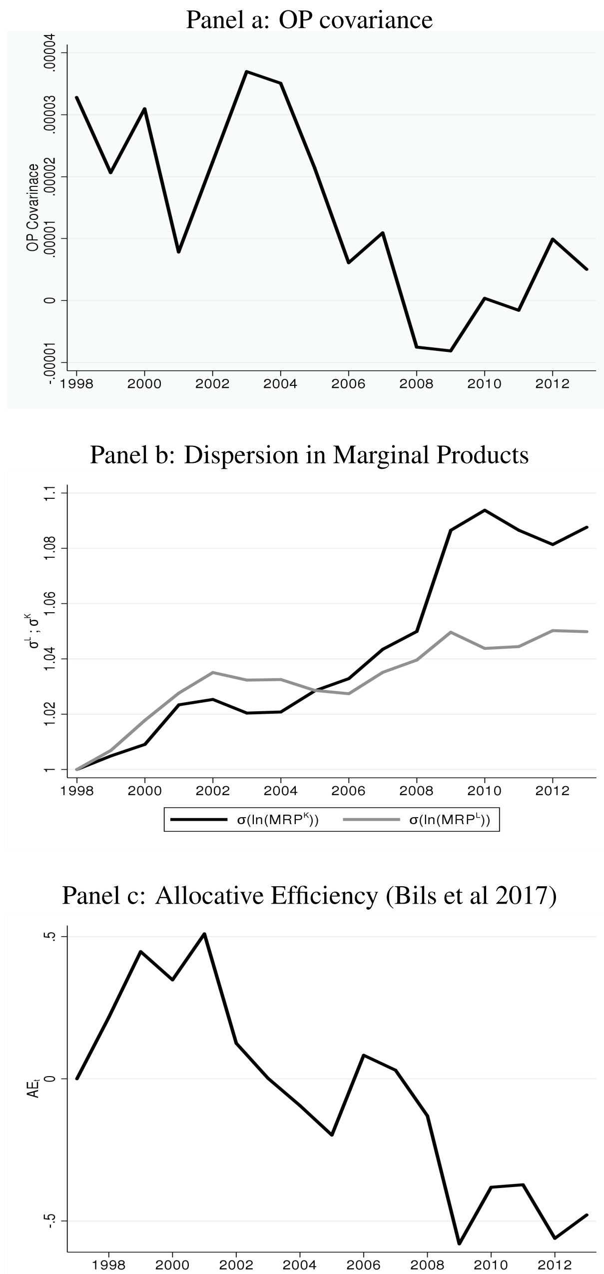
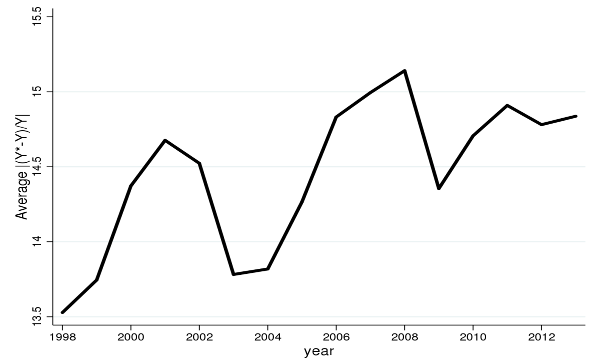


Figure A.15 (cont'ed): Alternative aggregate measures of efficiency of resource allocation

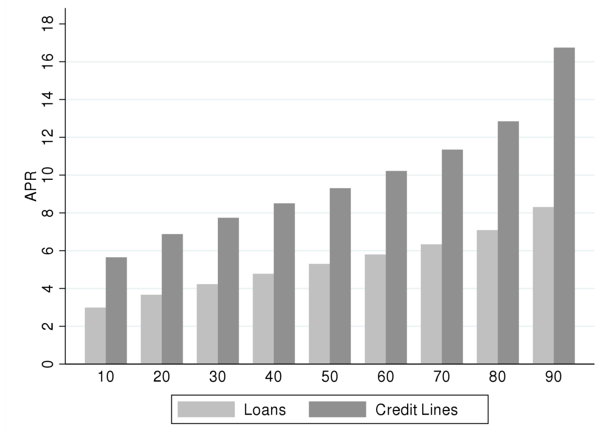
Panel d: Average Deviations from Target Output



These measures are computed in two steps. First, for each year, we calculate the standard deviation of log MRP^K (and log MRP^L) across firms that operate in a given 4-digits industry. Second, each year we calculate the aggregate dispersion as the weighted average of dispersions across industries. Each industry is given a time-invariant weight equal to its average share in value added measured in 1998. The constant weight allows us to isolate time-series changes in dispersion, net of changes in the relative importance of each industry over time. Panel b plots the OP-covariance term ([153]), showing a decline in the correlation between firm-level productivity (ω_{it}) and local market share ($\text{Revenues}_{ispt}/\sum_i \text{Revenues}_{ispt}$, s=industry and p=province). Panel c presents the inferred allocative efficiency using the aggregation formula developed in [154] (BKR). We closely follow the author in the construction of the aggregate efficiency term. We refer to the paper for the exact formulas and aggregation steps. We assume a value of $\varepsilon = 9$.[154] To focus on the time series dynamics, we normalize the value of the BKR measure in 1997 to zero. In panel d we plot the average absolute deviation of output from target output ($\sum_i \frac{1}{N_t} |(Y_{it}^* - Y_{it})/Y_{it}|$, N_t is the number of observations in year t) across the different years of our sample.

154. We also experiment with other values ($\varepsilon = 3$ and $\varepsilon = 11$) obtaining lower estimates of allocative efficiency but qualitatively similar trends.

Figure A.16. Distribution of APR on bank loans, credit lines and credit BBR



A.12.4 Alternative Measures of Users Costs

Alternative Interest Rates

Figure A.16 displays the distribution of the APR on term loans and on credit lines.

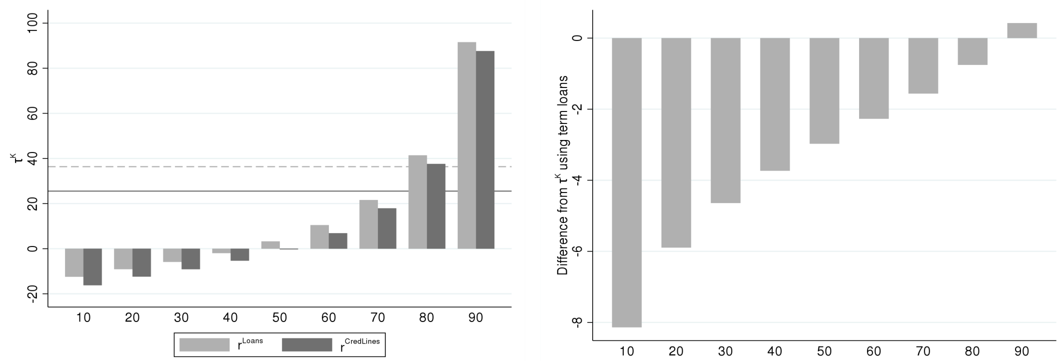
Figure A.17, panel a investigates how the distribution of τ_{it}^{K} would change using different interest rates to proxy for the cost of debt financing (loans VS credit lines). Figure A.17, panel b replicates panel a, but looking at the distribution of percentage deviations from target capital ($(K_{it}^{*} - K_{it})/K_{it}$).

Alternative Wages

Figure A.18, panel a investigates how the distribution of τ_{it}^{L} would change using wages of newly hired workers (average for each industry-province-year) to proxy for the user cost of labor. Figure A.19, panel b and c replicates panel a, but looking at the distribution of percentage deviations from target labor ($(L_{it}^{*} - L_{it})/L_{it}$).

Figure A.17. MRP-cost gaps and percentage deviations of capital user APR on credit lines

Panel a: MRP-cost gaps



Panel b: Percentage Deviation from Target Capital

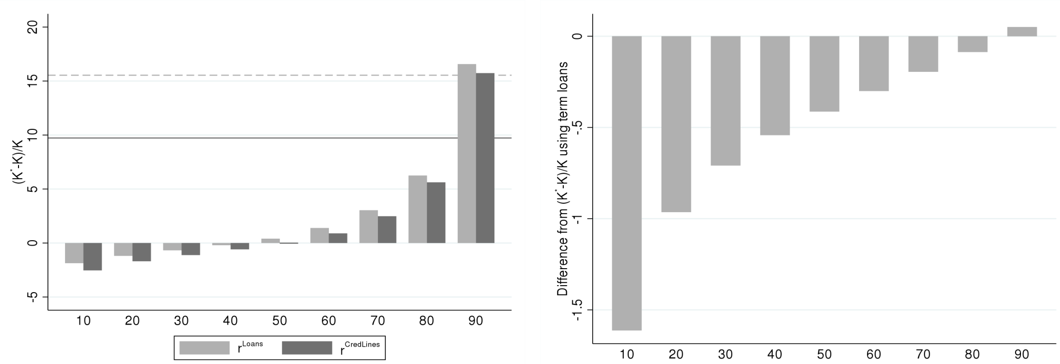
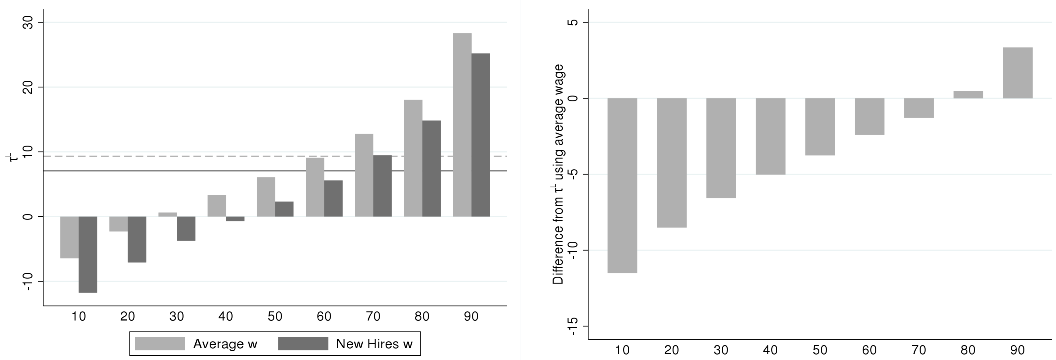


Figure A.18. MRP-cost gaps and percentage deviations using wages of newly hired workers

Panel a: MRP-cost gaps



Panel b: Percentage Deviation from Target Labor

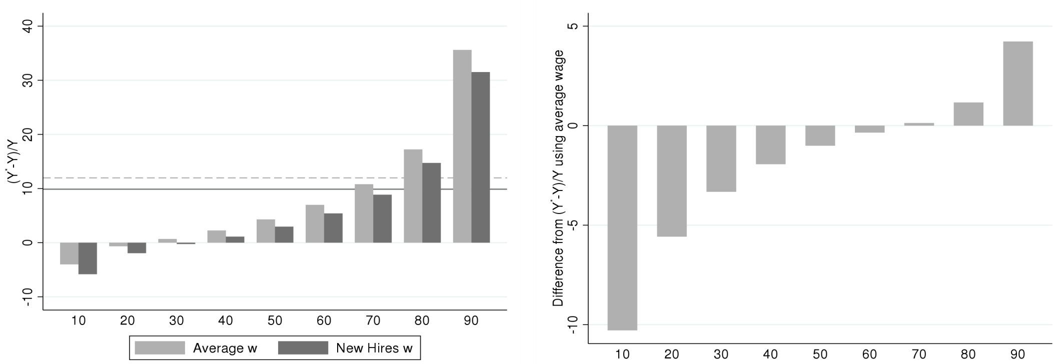
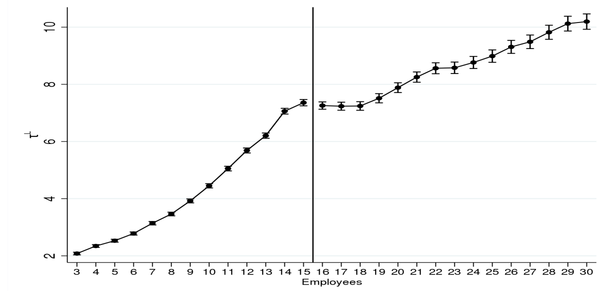
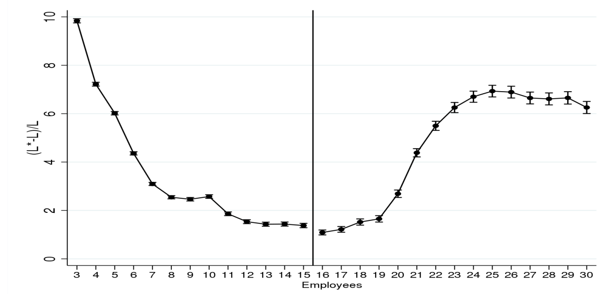


Figure A.19. Labor market frictions using wages of newly hired workers

Panel a: MRP-cost Gaps of Labor



Panel b: Employment Policy Distortions and Output Gap

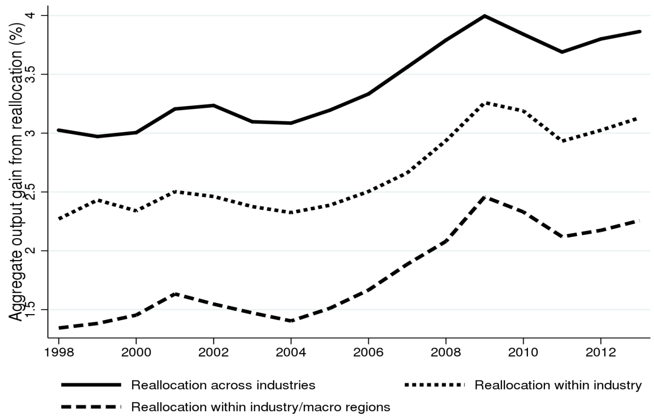


A.12.5 Aggregate Output and TFP Gains from Misallocation using Alternative User Costs

In the paper, we defined target capital and target labor endowments as the amount of capital and labor that would equalize the MRP of primary inputs to the user costs observed in the data (see Equation (1.11)). A concern with this exercise is that might actually overestimate $X^*$of firms with $\tau_{it}^X > 0$ (and underestimate X^* for those with $\tau_{it}^X < 0$), for $X = K, L$. For example, it might be the case that that the user cost of capital calculated using the APR on loans understates the marginal cost of debt finance. Similarly, the average wage might underestimate the wage paid to hire the marginal worker.

In this section, we use MRP-cost gaps (and corresponding deviations from target input demands) constructed using interest rate on credit line drafts and the wage of newly hired

Figure A.20. Reallocation with alternative user costs used to calculate target input and output



workers to investigate how our aggregate calculations are affected by our choice of interest rates and wages.

It is ex-ante unclear whether higher user costs produce higher or lower gains from reallocation, because two forces push in opposite directions. First, since the user cost of capital constructed using the interest rate on credit line drafts and the wage of newly hired workers are higher, the distribution of $(K^*_{it} - K_{it})/K_{it}$ and $(L^*_{it} - L_{it})/L_{it}$ shifts to the left. Second, because more firms will be operating with $K^*_{it} < K_{it}$ and $L^*_{it} < L_{it}$ as a result of the shift, there will a larger volume of resources that can be reallocated. Figure A.20 shows that the second force prevails. The black solid line shows the gains from reallocation using $r^{Credit\,Lines}$ to construct τ^K_{it}; the dotted line the gains when we use $w^{new\,hires}$ to construct τ^L_{it} ; the dashed line uses $r^{Credit\,Lines}$ and $w^{new\,hires}$ to construct τ^K_{it} and τ^L_{it}. While the gains from reallocation are higher, their relative magnitude in different periods of the business cycle is unchanged: increasing during the credit expansion post-Euro, and highest during the financial and sovereign crisis.

CHAPTER 3

THE BANK LENDING CHANNEL: IMPACT ON CREDIT SUPPLY AND THE REAL ECONOMY

Margherita Bottero[*], Simone Lenzu[†], and Filippo Mezzanotti[‡][1]

3.1 Introduction

Financial intermediaries play a fundamental role in enhancing economic growth, lending to firms and households and reallocating capital to the highest-value use ([179]; [180]). But loans are not the only assets held by banks. A large fraction of their portfolio is composed of securities, real properties, and equity holdings. While there are complementarities among these different investments, swings in the price and riskiness of these assets may lead to adjustments in banks' credit supply, with potential adverse effects on the real economy.

This paper studies the role played by banks' security portfolio in the propagation of macro-financial shocks originated outside national borders. Our focus is on the largest security class held by banks, sovereign bonds. We analyze credit market dynamics in Italy around the 2010 Greek bailout event. The bailout directly concerned Greece and its investors, but it also caused a widespread turmoil in the global sovereign market. We show

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that financial intermediaries more exposed to government securities significantly tightened their credit supply after this shock and that this credit contraction negatively affected the real activity of the Italian corporate sector.

This evidence on the role of securities in the propagation of an international shock into the economy represents a new channel through which the banking system can foster financial contagion across countries, complementing previous work that focused on funding linkages across countries ([181]) or examined the importance of international banks ([129, 182]). Our results show that this effect is sizable even when the securities are relatively safe and liquid, like in the case of government bonds. Moreover, our research highlights that the economic costs of credit crunch fall disproportionately on small enterprises, a subset of the economy that is very dependent on bank credit but it is often overlooked in the literature ([45]; [183]).

Our data include all Italian financial intermediaries and a large, representative sample of nonfinancial firms operating in the time window around the first Greek bailout in April 2010. To assess the impact of the tensions in sovereign markets on credit supply, and then on real outcomes, we analyze over 500,000 bank–firm credit relationships and compare the change in credit supply around the Greek bailout, across banks differentially exposed to government bonds.[2] To capture the exposure of financial institutions to the sovereign shock, we construct a bank-level proxy that exploits the cross-sectional heterogeneity in banks' holdings of Italian sovereigns measured *before* the Greek bailout. Furthermore, our research design takes advantage of the widespread presence of firms that established simultaneous lending relationships with different financial institutions to control for changes in firms' credit demand and creditworthiness ([130,184]; [44]; [18]). In practice, we run a

2. In our database, one observation corresponds to the difference between the average log credit granted by bank b to firm j during the period 2010:Q2-2011:Q1 and the average log credit granted by the same bank to the same firm during the period 2009:Q1-2010:Q1. This results in a total of almost 5 million observations in the quarterly firm–bank panel data set.

within-firm difference-in-difference regression that compares changes in credit supply to the same borrower from lenders with different exposure to Italian government debt.

The choice of this setting reflects three considerations. First, the Greek events fundamentally and unexpectedly changed the risk perception of government bonds issued by several other countries in Europe, including Italy. As we discuss in the paper, the sequence of events that culminated into Greece's bailout request was a "wake-up call" for investors inducing an increase in the volatility of government bond yields in peripheral European countries, and a widening of their spreads vis-a-vis the German Bund ([185]; [186]). As sovereign securities represent a large fraction of banks' assets, typically the second largest after loans, the shock had a sizable impact on their activity. Second, our measure of banks' exposure exploits only pre-crisis variation in sovereign holdings, allowing us to tackle endogeneity concerns related to banks' portfolio adjustments. In fact, as the situation began to deteriorate in spring 2010, intermediaries started to (endogenously) adjust their exposure to government securities ([187]). Finally, our event window excludes periods characterized by unconventional measures adopted by the ECB to counteract the dysfunctions in sovereign markets, which might confound the empirical analysis.[3]

We document that the negative shock to the sovereign bond market had a negative, causal effect on lending. When we compare lending to the same firm by two banks that are one standard deviation apart in terms of pre-crisis sovereign exposure, we find that the more exposed financial intermediary reduced its credit supply by 10% more relative to the other. Not only did the banks more exposed cut lending more intensively, but they were

3. In particular, in our main specifications we exclude from our estimation period the second half of 2011 when the ECB re-activated its Securities Markets Programme with the objective of restoring the smooth functioning of the European sovereign market. The reactivation of the SMP was followed by two other measures, two longer-term refinancing operations (LTROs) with an extended maturity of 3 years announced in December 2011, and the OMT, announced in July 2012 (see [188]). See also [189] for a study of the effect of the the LTRO on bank credit supply.

also more likely to reduce ongoing credit relationships or cut credit lines. Our results are robust to alternative measures of sovereign exposure and other potential confounding factors, such as bank–firm relation-specific characteristics. Furthermore, a battery of placebo tests and the lack of differential trends in lending growth before the shock confirm the causal interpretation of our results. Lastly, we can exclude any systematic sorting of firms experiencing high idiosyncratic shocks with banks more exposed to sovereigns.

Investigating the channels of transmission of the balance sheet shock, we find that the tightening in credit supply was larger for poorly capitalized banks and intermediaries relying more heavily on interbank debt as a source of funding. This suggests that sovereign shock affected lending because it unexpectedly increased the riskiness of bank assets, forcing financial intermediaries to adjust their lending behavior. In fact, sovereign securities, considered to be almost riskless before the Greek bailout, started carrying a nontrivial amount of credit risk after the spring 2010. As a result, banks concerned with the need to increase their capitalization or to raise funding preemptively tightened credit supply in order to adjust the riskiness of their assets ([182]; [129]). Furthermore, the turmoil in the government bond market also impaired banks' operations by reducing the collateral value of sovereigns ([190]), which are used extensively to back up collateralized interbank lending transactions. As in the case of the recent financial crisis ([191]; [47]), intermediaries' exposure to interbank markets appears to be a catalyst for the transmission of macro-financial shocks to the economy.

The contraction in credit supply caused by the sovereign shock had a sizable effect on firms' ability to access bank financing, both at the micro- and macro-level. We find that the lenders' exposure at the onset of the sovereign crisis is highly predictive of the change in a firm's *total* bank credit spanning the burst of the sovereign crisis. To one standard deviation increase in lenders' average holdings of Italian sovereign securities before the sovereign shock corresponds to a reduction of 5% in the firm's total bank borrowing, compared with its pre-crisis amount. This suggests that, because of credit-market imperfections, firms were unable to compensate the reduction in credit from more exposed lenders by expanding their borrowing from less exposed financial intermediaries. Conducting a simple counterfactual exercise, our estimates suggest that the lending channel caused by the turmoil in sovereign markets can account for a drop of almost 2% in aggregate lending. Furthermore, we show that the overall reduction in credit was stronger for smaller firms. While credit declined for both large and small companies, the effect on smaller enterprises was substantially larger. Since we find that banks did not ex ante cut smaller firms more extensively, this heterogeneous treatment effect can be explained by the inability of smaller firms to smooth the shock across different lenders. This result is consistent with smaller companies being more affected by informational frictions ([11]) and therefore having more issues with establishing or reinforcing credit relationships ([56]), especially during bad times.

The effects in the loan market translated into effects on real outcomes for borrowers. Mirroring the previous analysis, our test compares changes in firm policies – investments and payroll – across firms borrowing from intermediaries with different exposure to sovereigns at the onset of the crisis. To the extent that firm characteristics and investment opportunities are orthogonal with respect to lenders' bond holdings, this approach provides us with a direct proxy for the firms that are likely to become credit constrained in the aftermath of the crisis, overcoming the key identification problem in the real effects literature ([192]; [30]). We find that the sovereign shock negatively affected firms' investment and employment policies. This effect is fully driven by small companies, which cut investments and payroll costs more than other equally exposed large firms. In particular, we estimate a 38 cent decrease in investments and 37 cent decrease in payroll payments for every euro of funding cut to small firms. At the same time, we find essentially no effect for larger firms. Lastly, we perform a number of robustness checks to exclude the possibility that unobserved heterogeneity in investment opportunities or changes in credit demand -- rather than shifts in credit supply – may be the driving force behind our findings.

This paper has three main contributions. First, we show that the security portfolio of banks plays an important role in the propagation of international financial shocks. To explain how banks can facilitate contagions across countries, the previous literature has focused on the role of international interbank markets and on the importance of global financial intermediaries with operations across multiple countries (e.g., [129,181,193,194]). Our analysis highlights that the security portfolio of banks represents another significant factor exposing an economy to international risk. Importantly, given the high level of integration in financial markets, the risk of contagion coming from securities does not necessarily require a direct exposure to another country. For instance, Italian banks were only minimally exposed to Greek bonds but they were still affected by the Greek bailout through Italian sovereigns. We think of our estimates as a lower bound of the potential costs due to this channel, since the security class studied in this paper - sovereign bonds - is one of the least volatile in the portfolio of financial intermediaries. Furthermore, because securities are one of the most important asset class in banks' balance sheets ([195]), our analysis suggests that the scope of this "security channel" can be substantial during periods of distress.

Second, this work provides new evidence of the real economic costs of a banking system encumbered with government debt.[4] Other studies explored the real effects of the recent European sovereign crisis using data on large banks and large firms active in the

4. Some of these papers try to explain the increase in sovereign holdings on banks' balance sheets ([183]; [196]; [197]), while others examine the potential crowding out of private credit by government debt ([198]; [199]). [195] and [200] analyze more generally the role of sovereign assets on banks' balance sheets across countries. For a broader discussion on financial stability, see [201].

syndicated loan market ([202]; [203]).[5] Our paper differs from them along two dimensions. First, we study the implications of the sovereign crisis around the 2010 Greek bailout event. This setting is ideal because, by focusing on one specific shock originated outside the national borders, we can examine the effect of an increase in sovereign risk when this negative event is not caused by a contemporaneous deterioration in economic fundamental or political risk. Second, the granularity of our data allows us to improve upon the existing literature in terms of both internal and external validity. By combining loan-level data from the Italian Credit Register with bank-specific measures of sovereign exposure, we can effectively isolate the effects of the sovereign shock on banks credit supply from the effects imputable to a reduction in credit demand ([205]) or to a change in country-specific risk ([206]). Furthermore, the representativeness of our sample allows us to study the heterogeneous effects of the credit tightening across firms of different size. This feature is important because, as our results show, the investment and employment elasticities estimated for small firms may differ substantially from the ones estimated for large corporations.

Third, this paper contributes to the literature on the real effects of credit supply shocks by highlighting the large heterogeneity of such effects in the cross-section of firms ([67]).[6] Our results highlight that smaller companies pay a disproportionately larger price in the event of a credit crunch, even when they are not a directly target of credit cuts. This is because smaller firms are intrinsically more sensitive to changes in the availability of bank credit, having fewer funding options outside bank credit and experiencing more difficulties in establishing new banking relationships.

5. Another paper looking at the credit effect of the sovereign crisis is [204]. Similar to [203], the author uses bank-level data from the large European banks included in stress tests conducted by the ECB to explore the effects of the crisis on credit market outcomes.

6. In this area, we find particularly close to us those papers that examined the effect of the financial crisis, both in US ([207]; [45]; [208]; [17]) and Europe ([209]; [47]).

The remainder of this chapter is organized as follows. In Section 3.2, we review some background information about the European sovereign debt crisis. In Section 3.3, we describe the data used in the paper. In Section 3.4, we introduce and discuss our identification strategy, provide evidence of the presence of the bank lending channel, and document its heterogeneous effects across firms and banks. In Section 3.5, we show that the sovereign shock impaired firms' access to bank credit, consequently affecting their investments and employment. Section 3.6 concludes.

3.2 The Onset of the Sovereign Crisis

A key element in our study is the bailout request advanced by Greece in April 2010. The bailout represented a unique breaking point in sovereign markets and triggered the series of events that led to the European sovereign crisis. In particular, the Greek shock prompted a reassessment of the default risk for a number of countries in the European Union. This shock was arguably the biggest event in the monetary union since the adoption of the single currency and it directly affected financial intermediaries investing in sovereign securities of distressed countries.

Until late 2009 neither financial markets nor the media appeared to be particularly concerned with the sustainability of sovereign debt in peripheral European countries. Since the introduction of the euro, the yields of 10-year bonds issued by European countries had always been low and stable.[7] However, after the parliamentary elections held in Greece in October 2009, the newly elected government acknowledged budget misreporting in pre-

7. The convergence began right after the institution of the European monetary union and was interrupted only by a short-lived increase in the interest rates of peripheral countries in the second half of 2008 driven by bank bailouts in Ireland and Greece ([187]).

vious years. As a consequence, Greece had to recognize a larger-than-expected fiscal deficit, generating concerns about the health of the Greek economy and the solvency of its sovereign debt.[8] The situation became even more dramatic in the spring of 2010. On April 23, the Greek government requested an EU/IMF bailout package to cover its financial needs for the remainder of the year. A few days later, on April 27, Standard & Poor's downgraded Greece's sovereign debt rating to BB+ ("junk bond"). In response to these events, yields on Greek government bonds rose sharply, barring the country's access to capital markets.

The Greek crisis is regarded as a sovereign-risk *wake-up call* ([210], [186]), which increased investors' sensitivity to country-specific macroeconomic fundamentals and prompted a general reassessment of country-specific default risk across the euro area.[9] In particular, shortly after the events in Greece, investors began to be concerned with the solvency and liquidity of the public debt issued by other European countries, starting with Ireland and Portugal and spreading soon thereafter to Spain and Italy ([196]). Importantly, this shift in riskiness across European countries was not the result of negative domestic news, but instead it was the result of the general reassessment of sovereign risk caused by the Greek events.

The wake-up call narrative is in line with a large body of evidence ([183]; [212]; [190]), which finds that the Greek bailout represented an unexpected shock to sovereign-bonds

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8. After a series of upward deficit revisions, the Greek government estimated the deficit at 12.7 percent of GDP for 2009, up from 7.7 percent in 2008. See [185] for a detailed description of the European sovereign crisis.

9. The literature distinguishes among three types of international transmission of area-specific shocks: "wake-up call contagion", "pure contagion", and "shift contagion". See [211] for a review. [186] show that the Greek crisis was a wake-up call for investors who largely ignored macroeconomic fundamentals for peripheral EMU countries before the end of 2009. By contrast, they find no evidence of other forms of contagion.

markets.[10] Furthermore, the importance of this shock confirmed by a number of simple economic indicators. In Italy, the spread between the BTP and the German Bund (henceforth BTP–Bund spread) increased from 85 bps at the end of the first quarter of 2010 to almost 160 bps in the third quarter of the same year (Figure 3.1, panel a), and it continued to rise after this date. To put the economic magnitude of this change in perspective, this jump corresponds to an increase of almost two standard deviations in spread since 2005. Similarly, the CDS on Italian bonds with 5 years of maturity doubled soon after the bailout.[11]

The sudden change in the risk profile of government securities had a direct negative effect on the balance sheets of banks holding these assets. As we discuss later in the paper, this shock affected banks because it decreased the market value and liquidity of these government bonds and because it reduced the ability of financial intermediaries to use these securities as collateral in the wholesale funding market ([196]). Consistent with this idea, participants at the European Bank and Insurance CEO Conference in September 2010 stated that the fear that originated from sovereign markets was the biggest threat to bank share prices (Figure B.3).[12] The same survey showed that investors were ranking banks in countries most affected by the sovereign shock – Italy, Greece and Portugal -- among the financial institutions with the worst expected performance. This negative effect

10. [213] present a theoretical model that shows that unexpected events such as the Greek bailout may trigger a widespread increase in uncertainty with negative repercussions for other countries.

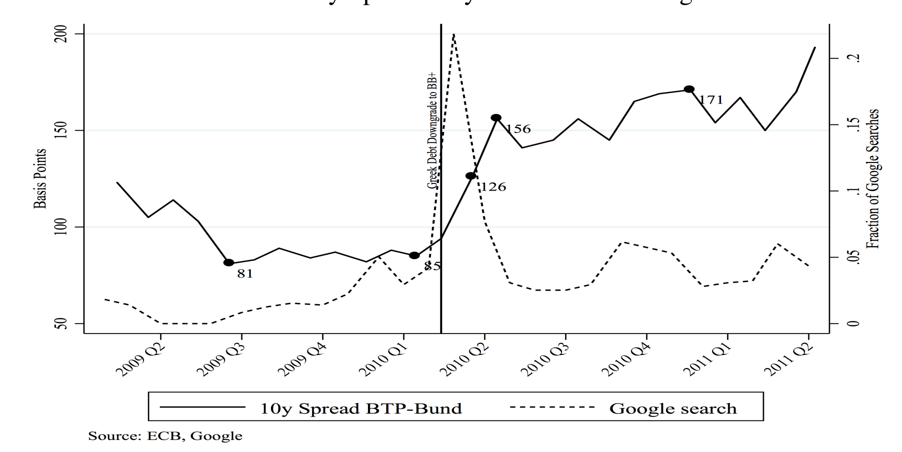
11. In line with this idea, we find that the correlation between the Italian and German spread was essentially one before October 2009, reflecting the fact that the spreads with Germany were negligible for all euro-area countries. Furthermore, in the months immediately before the bailout, it dropped substantially, driven by the rising yields on the Greek bond, and then increased again, as tensions spilled over to other European countries, driving upward the yields on their sovereign securities (Table B.4 in Appendix B.4).

12. “Competing in the age of austerity,” Bank of America Merrill Lynch Banking & Insurance CEO Conference, London, 29 September 2010. Source: http://ftalphaville.ft.com/2010/10/04/359726/european-bank-watch-past-present-and-future/

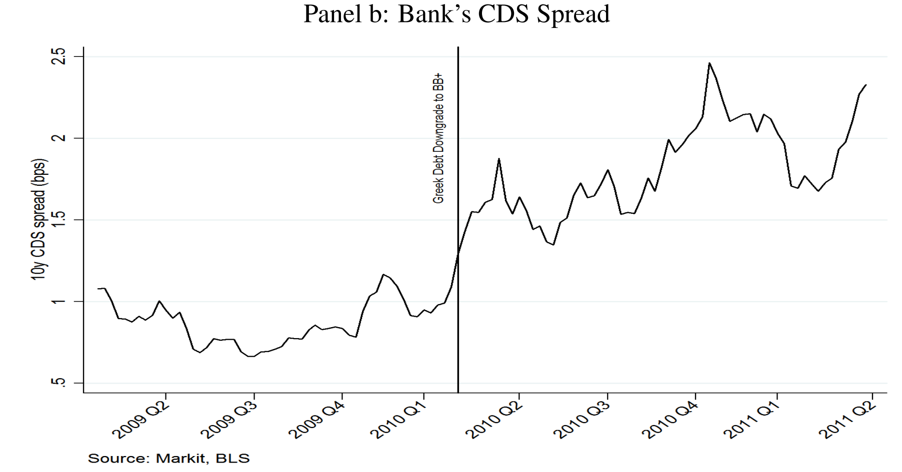
Figure 2.1. The burst of the sovereign crisis

Panel a shows, on the left-hand axis (solid line), the dynamics of the spread between the yield of 10-year Italian zero-coupon bonds and that of 10-year zero-coupon bonds issued by Germany. Data from ECB. On the right-hand axis (dashed line) the Figure displays the frequency of Google searches of key words "Euro Crisis" using Google Trends. The y-axis reports the Google searches in every week between the beginning of 2008:Q1 and the end of 2011:Q2 as a fraction of the total Google searches of the key words over the same period. Source: http://www.google.com/trends/. Sources: ECB, Google. Panel b reports the time series of the average of the CDS spreads on unsecured senior debt of the top 5 Italian banks (solid line). Data are taken from Markit database and include only the CDS issued in Euro. Sources: Markit.

Panel a: 10y Spread Italy and Media Coverage



Panel b: Bank’s CDS Spread



is confirmed by the CDS on bonds issued by large Italian banks, which spiked right after the news (Figure 3.1, panel b). In particular, looking at the quarters before and after the Greek bailout, the average spread of the top-five Italian banks rose by 78 percent, over 2.3 times its historical standard deviation. Using a wider set of banks, this result is also confirmed by [214]. Lastly, Italian banks also paid a higher cost in the interbank market lending after the Greek bailout ([190]).

While the events initiated by the Greek bailout had an unambiguous negative effect on the European economy and sovereign markets (e.g., [185]), it is still unclear to what extent this shock hurt the real economy by triggering a significant reduction in credit from highly exposed banks. In the rest of the paper, we employ data from the Italian Firm Register and Credit Register to examine this question.

3.3 Data

The building block for our database is Bank of Italy Credit Register, which contains detailed information on the credit relationships entertained by intermediaries operating in Italy. We match the Credit Register data with the Italian Census of corporations to obtain the balance sheet, income statement, industry, and headquarter location of borrowing firms.[13] The Bank of Italy supervisory records provide us with quarterly accounting information on balance sheets and income statements, and with a detailed picture on sovereign-bond holdings of each bank operating in Italy.

13. In the Credit Register, we observe relationships *in bonis* that exceeds the threshold of 30,000 euros. Positions in default need to be reported irrespective of their amount. The Census of corporations is proprietary database collected by Cerved Group S.p.A. See Appendix B.1 for a discussion about the data-construction process and variables used in this work.

We restrict most of our analysis to a two-year window around the Greek bailout. This window is split into a pre-crisis period – from 2009:Q2 to 2010:Q1 – and a post-crisis period – from 2010:Q2 to 2011:Q1. After applying standard filters and consolidating bank balance-sheet items, our final data set includes 527 different bank holding companies, over 185 thousand nonfinancial firms, and 534 thousand unique firm-bank credit relationships, for a total of more than 4.5 million observations between 2009:Q2 and 2011:Q1. Of this sample, 141 thousand firms established multiple lending relationships around the shock. Table 2.1 displays the summary statistics of the variables of interest, focusing on the subsample of firms with multiple lending relationships.[14]

The average firm in our data set is 16 years old at the end of 2009, and it has assets with book value of 6 million euros, and around 5.5 million euros in revenues. Companies with revenues below 2 millions – our definition of a small firm in line with the European Statistical agency – account for 67 percent of the sample. This sample is close to the full population of Italian banks and corporations, and it is well suited for our purpose of investigating the transmission of credit-supply shocks across heterogeneous types of firms. In particular, it allows us to cast light on the real effects on small firms, which are not monitored by rating agencies or the financial press and are typically under-sampled in the literature (e.g. [45]).

We use the stock of Italian government bonds at the end of 2010:Q1 scaled by risk-weighted assets ($\text{Sovereigns}_{2010Q1}$) as a bank-specific measure of financial institutions'

14. Appendix B.2 reports a detailed description of all variables. We present further details about the distribution of the most important variables in Appendix B. Table B.3 reports summary statistics for the full sample of firms that includes both multiple- and one-lending relationships firms.

Table 2.1: Summary statistics

This table reports the summary statistics of the relationship-specific (panel a), firm-specific (panel b), and bank-specific variables (panel c) used in our analysis analysis. It refers to the subsample of firms that established multiple lending relationships in the one-year window centered around the Greek bailout. See Section 3.3 and Appendix (B.2) for a detailed description of the variables.

Panel a: Relationship-specific Variables

Variable	Obs	Mean	Sd	Sd (within)	Sd (Between)	Pc10	Pc90
g(Loans)	478235	0.019	0.659	0.523	0.427	-0.556	0.667
g(Tot Credit)	478235	0.026	0.593	0.451	0.416	-0.462	0.657
g(Cred Lines)	478235	0.003	0.624	0.485	0.424	-0.545	0.605
1(Cut Credit)	478235	0.388	0.487	0.387	0.316	0.000	1.000
Δ ln(Loans)	478235	0.019	0.540	0.372	0.455	-0.474	0.627
Length Relationship$_{2010Q1}$	478235	31.016	21.378	17.237	12.906	7.491	62.569
Share Relationship$_{2010Q1}$	478235	10.214	5.780	3.793	4.658	2.000	17.000
Num Relationship$_{2010Q1}$	478235	3.721	1.528	0.000	1.355	2.000	6.000

Panel b: Firm-specific Variables

Variable	Firms	Mean	Sd	Pc10	Pc90
Assets$_{2009}$	141372	6061.865	59452.404	405.000	9478.000
Revenues$_{2009}$	141372	5530.914	46158.986	382.000	8905.000
Wage Bill$_{2009}$	141372	844.320	6071.124	54.000	1383.000
Age$_{2009}$	141372	16	12	3	32
Bank Leverage$_{2009}$	141372	40.830	27.303	9.199	77.331
Credit Score$_{2009}$	141372	5.130	3.782	2.000	7.000
gr(Empl)	141372	0.034	0.480	-0.399	0.453
gr(Inv)	141372	-0.003	0.630	-0.615	0.669

Table 2.1 (cont'ed): Summary statistics

Panel c: Bank-specific Variables

Variable	Banks	Mean	Sd	Pc10	Pc90
$\text{Sovereigns}_{2010Q1}$	527	0.245	0.299	0.039	0.521
$\text{Sovereigns/Assets}_{2010Q1}$	527	0.143	0.106	0.028	0.284
$\text{Sovereigns/Tier1}_{2010Q1}$	527	1.429	1.171	0.263	2.799
ROA_{2010Q1}	527	0.000	0.002	-0.001	0.002
Size_{2010Q1}	527	5.619	1.622	3.754	7.490
Tier1_{2010Q1}	527	0.166	0.095	0.086	0.267
Deposits_{2010Q1}	527	0.801	0.389	0.465	1.278
$\text{Liquidity}_{2010Q1}$	527	0.008	0.006	0.003	0.015
$\text{Net Interbank Debt}_{2010Q1}$	527	-0.084	0.149	-0.213	0.019
$\text{Bad Loans}_{2010Q1}$	527	0.039	0.033	0.007	0.075
BCC	527	0.776	0.417	0.000	1.000
$\text{Tot Sovereigns}_{2010Q1}$	527	0.248	0.301	0.040	0.521
$\text{Sovereigns PIIGS}_{2010Q1}$	527	0.246	0.299	0.039	0.521
$\text{Sovereigns PIGS}_{2010Q1}$	527	0.001	0.006	0.000	0.000
$\text{Sovereigns DE}_{2010Q1}$	527	0.001	0.006	0.000	0.000

exposure to the sovereign shock. In 2010:Q1, the average exposure of Italian banks to sovereigns was 25 percent, with a standard deviation of about 30 percent. As we discuss later, alternative definitions provide a comparable picture. Italian sovereign debt amounts, on average, to almost 99 percent of the banks' sovereign portfolio during this period. This high concentration is confirmed when we look at banks with the most diversified portfolios of sovereign bonds. A bank holding company located at the first percentile of the distribution of Italian sovereigns over total sovereigns allocated 58 percent of its sovereign portfolio to Italian government bonds in 2010:Q1. Appendix B.3 shows that the strong home bias of financial institutions in our sample is not a unique feature of Italian banking system, but rather a common feature of many European countries like Germany, France and Spain. These statistics are indicative of a high average exposure to the sovereign shock across the financial intermediaries.[15]

15. Alternative measures confirm the high exposure of the Italian banking sector to the sovereign shock (like total sovereign holdings and sovereign holdings of "peripheral" European countries) and different scal-

In the first part of the paper, our main dependent variable is the percentage change in average outstanding loans between the pre- and post-shock periods for every firm–bank credit relation in our data set. More precisely, we collapse the quarterly amount of credit granted to firm j by bank b to a pre-shock average (2009:Q2-2010:Q1) and a post-shock average (2010:Q2-2011:Q1). Then, we calculate the standardized growth rate between the two averages ([127]; [45]):

$$g(\text{Loans}_{bj}) = \frac{\text{Loans}_{bj,Post} - \text{Loans}_{bj,Pre}}{0.5 \cdot \left[\text{Loans}_{bj,Post} + \text{Loans}_{bj,Pre}\right]}$$

This growth rate is a second-order approximation of the log difference growth rate around 0; it is bounded in the range [–2,2], limiting the influence of outliers; and it accounts for changes in credit along both the intensive and extensive margins. We also construct a growth rate that considers only the change along the intensive margin ($\Delta ln(\text{Loans}_{bj})$ and a dummy variable that flags those relationship in place before the Greek bailout but cut afterwards (Cut Credit_{bj}).

Our empirical models include the following set of bank-level and relationship-level controls: bank profitability, size, capitalization, retail funding, interbank funding, liquidity, quality of lending portfolio, and status of the bank as a cooperative bank (BCC).[16] We control for the length of the lending relationship between a borrower and each of its lenders and for the contribution of each lender to the total bank debt of the borrower. All bank-specific and relationship-specific controls are measured at the end of the first quarter of 2010, i.e., the last quarter of the pre crisis period.

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ing variables (Tier1 and total assets). We show in the paper that our empirical results are generally unchanged when we use either one of them as a bank-specific proxy of exposure.

16. Cooperative banks are characterized by a different statutory objective, and potentially a different lending policy, than other banks. The presence of Cooperative is not an Italian *unicum*, but they are widely found across Europe and the US.

In the second part of the paper, we look at firm-level outcomes. We measure investment as the log change in fixed assets between 2009 and 2011 (gr(Inv)) and change in employment as the log change in wage bill (gr(Empl)). Information on firms' balance sheet, industry, age, revenues, credit rating, and geographical location comes from the Cerved database. To limit the influence of outliers, we winsorize the growth rate of credit, investment and employment at 1% level.

3.4 The Bank Lending Channel

3.4.1 Identification Strategy

We investigate the lending channel triggered by the sovereign shock by studying changes in the credit supply from before to after the Greek bailout (April 2010) across banks with different pre-bailout exposure to sovereign assets. We estimate the following first-difference regression model:

$$g(\text{Loans}_{bj}) = \beta_0 + \beta_1 \text{Sovereigns}_{b,2010Q1} + \Gamma \cdot X_{b,2010Q1} + \rho_j + \varepsilon_{bj} \qquad (3.1)$$

where $g(\text{Loans}_{bj})$ measures the change in loans from bank b to firm j before to after the Greek bailout; $\text{Sovereigns}_{b,2010Q1}$ is a measure of bank exposure to sovereign securities. $X_{b,2010Q1}$ is a set of bank controls, measured right before the Greek bailout (2010:Q1): bank profitability, size, capitalization, funding (both retail deposit and wholesale separately), liquidity, quality of lending portfolio, and status of the bank as a cooperative bank. These controls are particularly important in this setting, because pre-bailout sovereign assets are not randomly assigned across banks. Instead, the holding of these securities is a function of bank characteristics ([195]), which in turn can also be correlated with changes in the propensity to lend.[17]

A standard difference-in-difference estimator would deliver biased estimates of the bank lending channel coefficient β_1 when credit supply contractions caused by sovereign exposure are correlated with unobservable firm-specific changes in credit demand. For example, if banks with high sovereign exposure systematically lend to firms with negative demand shock, estimates of β_1 will be biased downward. This negative sorting between firms and banks may arise because of geographical or industry segmentation in credit markets, and it could falsely lead us to attribute demand-driven drops in credit to movements in credit supply.[18] This is particularly concerning in this setting given the importance of credit demand in Europe during this period ([205]).

Following [**?**], we address the identification problem by focusing on firms with multiple lending relationships and adding firm fixed effects (ρ_j).[19] This approach is equivalent to a within-firm difference-in-differences model, where intermediaries with lower exposure to government debt are used as the control group for banks with higher exposure. A negative and statistically significant value of the coefficient β_1 indicates the presence of the lending channel triggered by banks' sovereign holdings. In our favorite specification, we cluster standard errors at the bank level, which is the level of the treatment ([217]). We also

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17. See Appendix B.4 for more discussions on the relationship between sovereign holdings and other bank characteristics.

18. For example, consider the case of poor areas within a country. In these areas banks may end up holding more sovereign assets on average because of lower investment opportunities. At the same time, they will lend to local firms, which may be weaker and therefore more sensitive to sovereign shocks. A similar argument can be developed for banks specialized in specific industries.

19. Studying a number of countries, [215] and [216] report that firms borrowing from one bank is the exception rather than the rule. In the United States 55.5 percent of small and medium firms have more than one bank, and the median number of credit relationships established by them is two.

discuss how the results change with alternative clustering or using different outcome or treatment variables.

The validity of this identification strategy relies on the following conditions. First, financial institutions should not have anticipated the imminent transmission of the sovereign crisis to Italian debt and therefore adjusted their sovereign portfolio beforehand. If the shock to Italian sovereigns had been expected before the downgrade of Greece, holdings at 2010:Q1 might reflect strategic or precautionary adjustments undertaken in expectation of the imminent crisis. This adjustment would be a relevant confounding factor in our analysis. However, the stylized facts presented in Section 3.2 suggest that this was not the case. Before the downgrade of Greek debt neither financial markets nor the media were pricing the scenario of an imminent sovereign debt crisis in Italy and other peripheral European countries. Moreover, the origin of the tensions on Italian sovereigns can be traced back to large government deficits and high public debt rather than imputed to a structural weakness of the country's banking system ([187]; [196]; [185]). Lastly, there is no evidence across Europe of large adjustments in banks' sovereign holding before the Greek bailout ([183]), leaving us confident about the validity of this first identification assumption.

The second identifying assumption of our design is the parallel-trend assumption. In other words, it must be true that, in the absence of the sovereign crisis, financial institutions with higher sovereign holdings (the treated group) would have displayed a credit supply trend comparable to banks with lower holdings (the control group). While the parallel trend assumption is fundamentally untestable due to the lack of an observable counterfactual, the next section presents extensive indirect evidence that supports it.

3.4.2 The Bank Lending Channel

Main Results – We start by presenting our main results, which are reported in Table 2.2.

Table 2.2: The bank lending channel

This table examines the transmission of the sovereign shock to credit supply via the bank lending channel. The outcome variable is the normalized growth rate in loans (g(Loans)) granted by bank *b* to firm *j* between (2010:Q2-2011:Q1) and (2009:Q2-2010:Q1). The main independent variable is the stock of Italian sovereigns held by the lender at the end of 2010:Q1 scaled by RWA ($Sovereigns_{2010Q1}$). All regressions include a set of bank-specific controls measured at the end 2010:Q1. Column (1) and (4) include a constant. Column (2) and (3) are within-firm estimates and include firm fixed effects. The models in Column (1)-(3) are estimated on the sample of firms with multiple lending relationships. The model in Column (4) includes single- and multiple-relationship firms. Column (3) and (4) include relationship-specific controls measured at the end 2010:Q1. Standard Errors are clustered at bank level. *** denotes significance at the 1% level, ** at the 5%, and * at the 10%.

	(1)	(2)	(3)	(4)
	g(Loans)			
$Sovereigns_{2010Q1}$	-0.220**	-0.259***	-0.345***	-0.309**
	(0.088)	(0.098)	(0.129)	(0.124)
ROA_{2010Q1}	4.706	8.913	7.324	4.923
	(8.899)	(10.679)	(11.534)	(9.767)
$Size_{2010Q1}$	0.003	0.004	0.006	0.007
	(0.006)	(0.007)	(0.008)	(0.007)
$Tier1_{2010Q1}$	0.733***	0.748***	0.905***	0.785***
	(0.249)	(0.258)	(0.282)	(0.276)
$Deposits_{2010Q1}$	0.160***	0.171***	0.168**	0.140**
	(0.060)	(0.065)	(0.074)	(0.070)
$Liquidity_{2010Q1}$	5.733	5.382	5.574	4.669
	(3.877)	(4.667)	(5.314)	(4.080)
Net Interbank $Debt_{2010Q1}$	0.183*	0.197*	0.126	0.115
	(0.100)	(0.112)	(0.174)	(0.172)
Bad $Loans_{2010Q1}$	-0.623***	-0.706***	-0.339	-0.205
	(0.212)	(0.207)	(0.349)	(0.349)
BCC	0.035	0.043	0.068*	0.072**
	(0.027)	(0.030)	(0.036)	(0.032)
Firm Fixed Effect	N	Y	Y	N
Relationship Controls	N	N	Y	Y
Observations	478235	478235	478235	533904
R-squared	0.003	0.372	0.387	0.044

In the first column, we investigate the relationship between sovereign exposure and credit supply in a simple OLS model. In other words, we estimate model (3.1) without including the firm fixed effect ρ_i. We find that exposure to the sovereign market before the Greek bailout significantly predicts lower credit to firms. As previously explained, this result could potentially be driven by a contemporaneous, unobservable decline in firms' credit demand. To address this concern, we augment our model with firm fixed effects (Column 2). This specification only exploits within-firm variation, comparing changes in credit provided to the same firm by different intermediaries. Also in this case, we find a negative relationship between sovereigns and credit. The magnitude of β_1 is larger, but the increase is not statistically significant.

Then, Column 3 shows that this result is not affected by heterogeneity across intermediaries in the nature of the credit relationship established between banks and firms. Because information about firms' fundamentals is durable and not easily transferable, firms with strong lending relationships are expected to be rationed less than others ([56,112,114]). Thus, our previous results may be biased upwards if banks with higher sovereign holdings systematically establish "weak" credit relationships with their borrowers. Augmenting our regressions with a set of relationship-specific variables that capture the pre-shock length and strength of the lending relationship between bank b and firm j strengthens the estimated lending-channel effect.

These findings suggest that exposure to distressed sovereigns had a sizable impact on the credit supply of financial intermediaries. On average, if we compare lending to the same firm by two banks that are one standard deviation apart in terms of exposure to distressed sovereigns, we find that the more exposed lender cut credit by about 10% more than the less exposed one. This increase corresponds to more than 20% of the (within-firm) standard deviation in credit over this period. Importantly, since we are exploiting only within-firm variation, this effect is capturing only variation in the supply of credit holding constant the firm's credit demand.

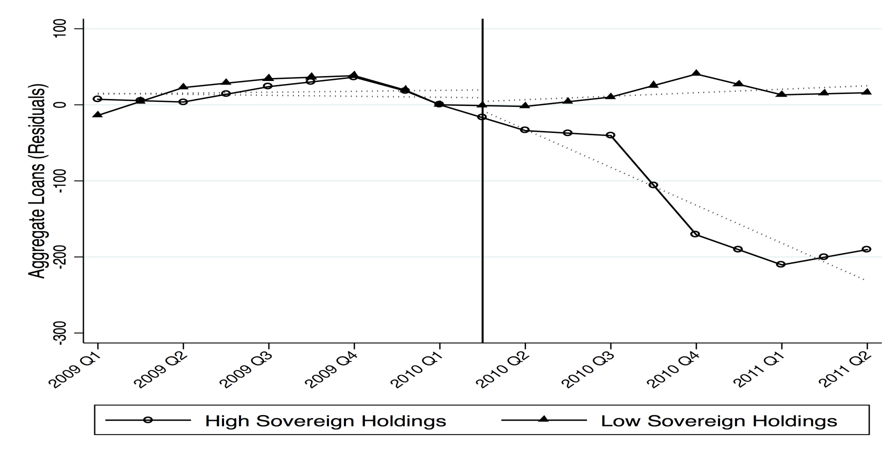
Before moving on with our analysis, we want to highlight two other important results. First, the lending channel triggered by banks' exposure to sovereigns is not confined to firms that engage in multiple lending relationships. To make this point, we estimate the model without firm fixed effects on the full sample, including both firms with one and multiple lenders in the pre-shock period (Table 2.2, Column 4). The relationship is still highly significant and comparable in terms of magnitude. For completeness, Table B.7 in the Appendix replicates all the different specifications with the full set of firms. Second, adding or removing firm fixed effects to control for credit demand does not significantly affect the magnitude of the lending channel coefficient. This result does not imply that credit demand was not important to explain the variation of credit during this period. Instead, it suggests that the level of correlation between changes in demand and supply at the firm level is not a sizable force in our setting. We will discuss the implication of this result for the identification of the real effects of the sovereign shock.

Robustness Tests – As discussed in the previous section, a causal interpretation of our analysis relies on the validity of a parallel-trend assumption. We now provide evidence in favor of this hypothesis by showing that (i) bank's differential exposure to sovereigns did not predict differential lending patterns before the Greek bailout; (ii) right after the shock, banks more exposed to sovereigns started decreasing their supply of credit.

We start by showing that these patterns hold at the aggregate level. First, we sort banks into a *"High Sovereign"* group and *"Low Sovereign"* group based on whether their pre-shock (conditional) holdings of Italian sovereigns place them above or below the median. Second, for consistency with the rest of the analysis, we extrapolate the quarterly variation in credit of bank b to firm j that cannot be explained by bank characteristics. Then, we

Figure 2.2. The bank lending channel

This Figure illustrates the bank lending channel semi-parametrically by comparing lending to firms from banks with high holdings of Italian sovereign bonds, the most exposed to the sovereign shock, and banks with lower holdings. See appendix B.6 for a detailed description of the procedure use to construct this figure.



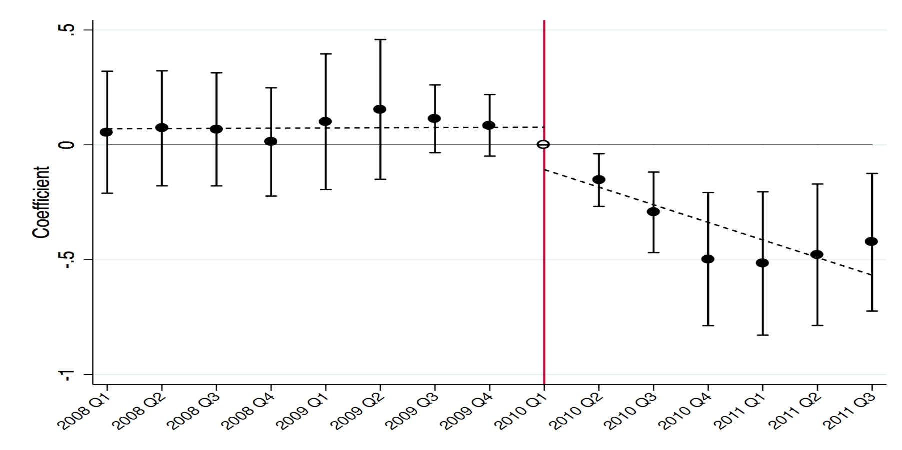
aggregate the residuals of corporate loans granted by "High Sovereign" and those granted by "Low Sovereign" banks, and plot them over time (Figure 3.1).[20] Appendix B.6 provides a detailed description of the procedure followed to conduct this semi-parametric test. Overall, we find that, before the sovereign shock, aggregate credit provided by the institutions with high and low holdings displays a very similar dynamic. However, after April 2010 the two groups start diverging. More exposed intermediaries cut lending more extensively, while the credit supply of less exposed banks does not react. These patterns present first evidence in favor of the parallel-trend assumption.

To address the concern that more exposed banks might have experienced a more severe reduction in credit demand, we turn to the micro-data. Using the econometric model in Equation (3.1) we perform the following parametric test of the parallel trend assumption:

20. The two time series are normalized such that aggregate lending is zero in 2010:Q1 for each group.

Figure 2.3. Pre-trending test

This Figure presents a graphical test of the pre-trending assumption behind our identification strategy. It plots the coefficient capturing the correlation of sovereign bonds holdings in quarter 2010:Q1 ($\text{Sovereigns}_{b,2010Q1}$) - our proxy of the bank balance sheet shock - and the growth rate of credit between quarter t and the last quarter before the sovereign shock: $g(\text{Loans}_{bj,t}) = \frac{\text{Loans}_{bj,t} - \text{Loans}_{bj,2010Q1}}{0.5 \cdot [\text{Loans}_{bj,t} + \text{Loans}_{bj,2010Q1}]}$. Quarter t is reported on the x-axis. All regressions are run on the sample of firms who established multiple lending relationships, and include bank-level and relationship-level controls measured in 2010:Q1, and firm fixed-effects. 95% confidence intervals are displayed. Standard errors clustered bank level.



$$g(\text{Loans}_{bj,\tau}) = \beta_{0\tau} + \beta_{1\tau}\text{Sovereigns}_{b,2010Q1} + \Gamma_\tau \cdot X_{b,2010Q1} + \rho_{j\tau} + \varepsilon_{bj\tau}$$

where the left-hand-side variable now measures the growth rate of credit from bank b to firm j between quarter τ and quarter 2010:Q1. Figure 3.1 plots the coefficient β_1 over time. Coefficients are reported as z-scores to facilitate comparison across periods. The results are line with the intuition provided by the aggregate test of Figure 3.1. Before the Greek bailout, we find no significant differences in credit supply between banks who were differently exposed to sovereigns at the onset of the crisis. Conversely, the graph displays a significant and long-lasting effect of the balance shock immediately after the Greek bailout. All in all, this evidence suggests that banks with lower sovereign holdings represent a valid control group for more exposed intermediaries, providing strong support for the identifying assumptions behind our empirical strategy.

Table 2.3: Bank lending channel: Alternative outcomes and alternative definition of sovereign shock

In this table we explore the bank lending channel for alternative measures of change in bank credit (Panel a) and alternative definitions of the sovereign shock incurred by lenders (Panel b). In Panel a, we consider four alternative measures of bank credit. In Column (1) we focus only on the percentage change in the credit lines granted by bank b to firm j before-to-after the Greek bailout; In Column (2) the percentage change total amount of bank credit, including credit lines and term loans; In Column (3) the dependent variable is a dummy variable equal one when a relationship in place in the pre-shock period is terminated in the post shock period; in Column (4) the the left hand side is the before-to-after log-change in term loans. The main independent variable is the exposure of the lender to Italian sovereigns ($\text{Sovereigns}_{2010Q1}$). In Panel b, the outcome variable is the normalized growth rate in loans (g(Loans)). We use two alternative measures of the sovereign shock incurred by each lender: the stock of Italian sovereigns held by the lender at the end of 2010:Q1 by total assets (Columns (1)-(4)) and by Tier1 (Columns (5)-(8)). All regressions in this Table include a set of bank-specific and relationship-specific controls measured at the end 2010:Q1. Every specification contains firm fixed effects and it is estimated on the sample of firms with multiple credit relationships. Standard Errors are clustered at bank level. *** denotes significance at the 1% level, ** at the 5%, and * at the 10%.

Panel a: Alternative outcomes

	(1)	(2)	(3)	(4)
	g(Cred Lines)	g(Tot Credit)	1(Cut Credit)	Δ ln(Loans)
$\text{Sovereigns}_{2010Q1}$	-0.357***	-0.324**	0.276***	-0.339***
	(0.128)	(0.128)	(0.092)	(0.121)
Firm Fixed Effect	Y	Y	Y	Y
Bank Controsl	Y	Y	Y	Y
Relationship Controls	Y	Y	Y	Y
Observations	478235	478235	478235	389007
R-squared	0.443	0.412	0.388	0.515

We conduct several tests to evaluate the robustness of our results.[21] First, we show that our results are similar when looking at alternative outcomes (Table 2.3a).

Considering a purely intensive margin ($\Delta ln(\text{Loan}_{bj})$), we find effects that are similar in magnitude to our main results. Repeating the same comparison across two banks one standard deviation apart in terms of exposure to distressed sovereigns, the more exposed lender cut credit by about 10% more than the less exposed one. Along the extensive margin, we also find that more exposed banks were more likely to cut credit. In particular, one standard deviation in exposure led to an increase by 8% in the probability of a decrease in

21. Most of the results in this section are presented in the Appendix, where we also provide more detail about the analysis.

Table 2.3 (cont'ed): Bank lending channel: Alternative outcomes and alternative definition of sovereign shock

Panel b: Alternative definition of sovereign shock

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	g(Loans)							
Sovereigns/Assets$_{2010Q1}$	-0.375**	-0.450***	-0.516**	-0.450**				
	(0.153)	(0.171)	(0.245)	(0.227)				
Sovereigns/Tier1$_{2010Q1}$					-0.023***	-0.030***	-0.042***	-0.035***
					(0.008)	(0.010)	(0.013)	(0.013)
Firm Fixed Effect	N	Y	Y	N	N	Y	Y	N
Bank Controsl	Y	Y	Y	Y	Y	Y	Y	Y
Relationship Controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	478235	478235	478235	533904	478235	478235	478235	533904
R-squared	0.003	0.372	0.387	0.043	0.003	0.372	0.387	0.044

the loan balance. Furthermore, we show in Table 2.3a that our main results are unchanged when looking at alternative definitions of bank credit. While our main results are estimated using term loans, the same analysis using only credit lines or total credit, i.e., credit lines plus term loans, is very similar in both statistical and economic magnitude.[22]

Second, we show that the estimates presented above are not driven by our measure of banks' sovereign exposure. Table 2.3b shows that the effects of the balance-sheet shock on credit supply is still significant and similar in economic magnitude if we scale banks' exposure to Italian sovereigns by alternative proxies of size – Total Assets and Tier1 capital. Similarly, our results are unchanged if we measure sovereign exposure using the overall sovereign portfolio or using government debt issued by Greece, Ireland, Portugal, Spain and Italy, all of which experienced tensions during the post-bailout period (Table 3.1). Interestingly, the results are also stable when we examine the effect of the exposure to Italian sovereigns, controlling simultaneously for exposure to other distressed countries, Greece, Ireland, Portugal and Spain. In Column (5) we find that exposure to other sovereign assets experiencing distress over this period also negatively affects the credit supply. This effect is only marginally significant, probably because the majority of Italian banks hold a negligible amount of non-Italian sovereign assets.[23]

Third, our findings are robust to different assumptions about the covariance structure of the errors. We believe that clustering standard errors at the bank level is the most appropriate and conservative choice, since it accounts for the fact that the variation of the shock variable is at the bank level. For completeness, we present in Table B.8 our main results clustering the standard errors at the firm level. Not surprisingly, we find that clustering

22. The data from the Italian Credit Register are in line with the patterns documented in [218], as more than 90 % (85% in the US) of the firms in our sample have at least one line of credit available.

23. The average Italian bank at 2010Q1 had about 99% of its sovereign assets invested in Italian debt. The median bank invested 100% of its sovereign portfolio in Italian bonds.

Table 2.4: The bank lending channel: different sovereign holdings

This table examines the bank lending channel using alternative measures of sovereign exposure. The outcome variable is the normalized growth rate in loans (g(Loans)) The main independent variables are different measures of bank's exposure to the sovereign crisis. In Column (1) we use the stock of Italian sovereigns over RWA; In Column (2) the stock of total GIPS sovereigns (Greece, Ireland, Portugal, and Spain) over RWA; In Column (3) the stock of GIPSI sovereigns (GIPS plus Italy) over RWA; In Column (4) we use total the stock of sovereign securities over RWA; Column (5) presents includes both the Italian sovereigns and GIPS sovereigns. All proxies of exposure are measured at the end of 2010:Q1. All regressions include a set of bank-specific and relationship-specific controls measured at the end 2010:Q1 Every specification contains firm fixed effects and it is estimated on the sample of firms with multiple credit relationships. Standard Errors are clustered at bank level. *** denotes significance at the 1% level, ** at the 5%, and * at the 10%.

	(1)	(2)	(3)	(4)	(5)
	g(Loans)				
$\text{Sovereigns}_{2010Q1}$	-0.345***				-0.302**
	(0.129)				(0.123)
Sovereigns PIGS_{2010Q1}		-0.580**			-0.480*
		(0.282)			(0.273)
Sovereigns PIIGS_{2010Q1}			-0.344***		
			(0.130)		
Tot $\text{Sovereigns}_{2010Q1}$				-0.344***	
				(0.129)	
Firm Fixed Effect	Y	Y	Y	Y	Y
Bank Controsl	Y	Y	Y	Y	Y
Relationship Controls	Y	Y	Y	Y	Y
Observations	478235	478235	478235	478235	478235
R-squared	0.387	0.387	0.387	0.387	0.387

errors at bank level produces substantially larger standard errors.[24] This is true across the whole set of results.

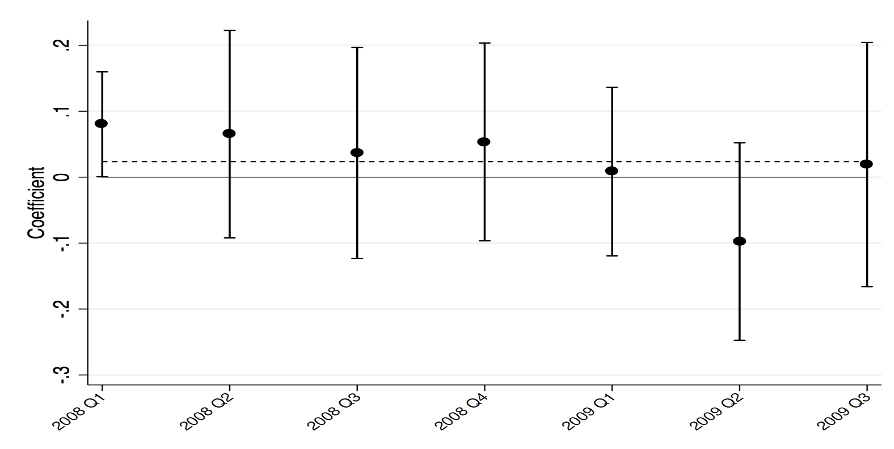
Fourth, we can rule out that our results are driven by differences in the governance structure across banks more and less exposed to sovereign securities, rather than by the sovereign exposure per se. Our concern is that differences in governance may be correlated both with sovereign exposure and lending patterns around the Greek bailout. In order to study this dimension, we consider two extreme cases – cooperative banks and foreign banks – and we estimate our baseline model interacting the treatment variable with a dummy flagging these two categories of banks. As shown in Table B.7 in the Appendix, we find that the lending behavior of either group of banks is not different than the average bank in our sample, as both interaction coefficients are small in size and not significant.

Lastly, we run a battery of placebo tests to rule out the possibility that the results presented in this paper reflect a "structural" negative correlation between holding of sovereigns in period $t-1$ and future credit supply. In fact, one might argue that reduction in credit supply typically follows an increase in sovereign holdings, independently of the conditions of sovereign markets. Using our preferred specification (model (3.1)), Figure 2.4 plots the coefficient capturing the correlation of sovereign-bond holdings in quarter $t-1$ ($\text{Sovereigns}_{b,t-1}$) and the average growth rate of credit $g(\text{Loans}_{ib,t})$ in the four quarter before and after t. All regressions include bank-level and relationship-level controls measured in time $t-1$ and firm fixed effects, as in the main specification. Furthermore, to avoid cherry-picking one specific period in which we run the test, we implement this placebo test independently for every quarter between the beginning of 2008 and the end of 2009. Before the sovereign crisis, we find a weak and statistically non significant correlation between sovereign holdings in $t-1$ and changes in credit supply before the Greek default, a period

24. When we employ the full panel dimension of our data – as in Figure 3.1 – we can also adjust errors at both the bank and the quarter level ([219]) without affecting the statistical significance of our inference.

Figure 2.4. Sovereign holdings and credit supply dynamics

This figure investigates the relationship between the stock of sovereigns in bank's portfolio and credit supply dynamics. It plots the coefficient capturing the correlation of sovereign bonds holdings in quarter $t-1$ ($\text{Sovereigns}_{b,t-1}$) and the the moving average growth rate of credit: $g(\text{Loans}_{bj,t}) = \frac{\bar{\text{Loans}}_{bj,t\to t+3} - \bar{Loans}_{bj,t-4\to t-1}}{0.5\cdot\left[\bar{\text{Loans}}_{bj,t\to t+3} + \bar{Loans}_{bj,t-4\to t-1}\right]}$, where $\bar{\text{Loans}}_{bj,t\to t+3} = 0.25\cdot\sum_{\tau=0}^{3}\text{Loans}_{ib,t+\tau}$ and $\bar{\text{Loans}}_{bj,t-4\to t-1} = 0.25\cdot\sum_{\tau=-1}^{-4}\text{Loans}_{ib,t+\tau}$. Quarter t is reported on the x-axis. All regressions are run on the sample of firms who established multiple lending relationships, and include bank-level controls and relationship-level measure in quarter t, and firm fixed effects. 95% confidence intervals are displayed. Standard errors clustered bank level.



characterized by no tension in sovereign markets. A joint significance test fails to reject the null hypothesis that the battery of yearly coefficients associated with $\text{Sovereigns}_{b,t-1}$ are zero. Furthermore, on average the main coefficient is actually positive.[25] Instead, it is only after the events in Greece that bank's holdings of sovereign securities predict a subsequent credit tightening. This result confirms that our estimates truly reflect the effects of a change in sovereign market conditions on bank lending, and it does not capture some structural relationship between sovereigns and lending.

The Transmission Mechanism of the Sovereign Shock – It is important to understand why banks more exposed to sovereign securities tighten their credit supply more than other, less exposed institutions. There are two main channels through which a shock to

25. Therefore, if anything, these results suggest that, in normal times, financial institutions use government bonds as a storage of liquidity in expectation of future investment opportunities ([195]).

the security portfolio can affect lending policies of financial intermediaries. The first channel is related to a bank's capital position (*capital channel*). A weaker balance sheet might induce bank managers – who are concerned with the future funding costs or long-term insolvency of the institution – to reduce the amount of assets at risk by shrinking the loan portfolio ([182]; [129]). In principle, one may think that the capital channel should not be particularly large for sovereign assets, as these securities did not required marked-to-market accounting under the regulatory framework in effect at the time. However, there are two important factors to consider when evaluating this argument. First, even if accounting capital is unchanged, a decline in the economic value of the assets should still trigger a reaction from the bank, since the economic capital is what matters for medium- and long-run portfolio choices of financial intermediaries ([196]).[26] Second, only sovereign assets classified in the held-to-maturity (HTM) portfolio were exempted from being marked-to-market, while sovereigns in the trading portfolio and available-for-sale (AFS) were valued based on market conditions (IAS 39).[27] Data from the 2010 European stress test shows that a large fraction of sovereigns owned by financial intermediaries was not held in the HTM portfolio.[28] For instance, only 34% of sovereign in large banks were classified in the HTM portfolio, with the remaining assets split between trading (23%) and AFS (43%).[29]

26. Referring precisely to the Euro crisis, [196] highlights that "whether securities are booked at market value or amortised cost makes little difference when bank's creditors become concerned about a possible default of the bank. In that case, creditors will lookt hrough accounting conventions, assessing the solidity of the bank based on its assets at market value (...)."

27. Clearly, changes in market price for assets in these two latter portfolios have distinct implications for the income statement.

28. However, note that Bank of Italy - with a temporary provision - decided that since June 2010 banks had the option to to neutralize gains and losses on ASF securities by accounting them at [historical] cost.

29. These statistics are constructed as calculating the value-weighted average across all sovereigns for the 91 banks that participated to the 2010 European Stress Tests (data collected using SNL). Using only Italian banks, we obtain very similar estimates. Since the snapshot refers to December 2010, the numbers potentially

Considering these caveats, the economic importance of the capital channel remains an empirical question. In particular, if the capital channel is at work, we expect - ceteris paribus - banks with a thinner capital buffer to be more responsive to the shock than other better capitalized institutions.

Alternatively, a drop in the market value of banks' security portfolio may affect their lending policy because it reduces the amount and quality of collateral available for borrowing in the inter-bank network (*collateral channel*). Following the same logic as before, the relevance of this channel can be tested by studying whether banks that are active borrowers in inter-bank markets or that have access to less stable funding respond more strongly to the sovereign shock.

We bring these alternative explanations to the data. To proxy for the weakness of the balance sheet, we use a measure based on bank's Tier1 ratio. We define a dummy variable – Low Capital Ratio_{2010Q1} – which takes a value of one when the Tier1 ratio is below 10%, very close to the regulatory boundary at the time (8%). This variable accounts for the fact that the capital channel is nonlinear and it is expected to be stronger for those institutions closer to the regulatory threshold. To capture exposure to the collateral channel we use the deposit-to-RWA ratio (Deposits_{2010Q1}) and the interbank borrowing-to-RWA ratio (Net Interbank $\text{Borrowing}_{2010Q1}$) ([191]; [47]). All bank variables are measured before the shock to avoid capturing mechanical or endogenous responses. We first consider one variable at a time and then look at them together in a horse-race specification.[30]

In the single-interaction model, we find evidence for both channels (Table 3.1). In particular, the effect of the balance sheet is magnified by the lack of capital at the bank

under-estimate the actual size of HTM assets, if banks have started to reclassify securities in that portfolio after the onset of the crisis.

30. The regression model always controls for the direct effects of the bank characteristics used as a proxy for different transmission channels; Table 3.1 reports only the interaction terms for expositional purposes.

Table 2.5: The bank lending channel: transmission mechanism

This table investigates the channels of transmission of the sovereign shock through banks' balance sheet. We interact exposure to the sovereign shock with a set of bank characteristics which are proxies for alternative balance sheet channels of transmission. All interaction variables are also included as a control in the regression. The outcome variable is the normalized growth rates in term loans (g(Loans)). The independent variables of interest are the exposure of the lender to Italian sovereigns (Sovereigns$_{2010Q1}$), and its interactions with different proxies of the transmission channels. All regressions include a set of bank-specific and relationship-specific controls are measured at the end 2010:Q1. The interaction variables include: close capital (dummy equal 1 if Tier1 ratio of the bank is between 8 and 10 percent); net borrower in interbank markets; deposit over RWA. Every specification contains firm fixed effects and it is estimated on the sample of firms with multiple credit relationships. Standard Errors are clustered at bank level. *** denotes significance at the 1% level, ** at the 5%, and * at the 10%.

	(1)	(2)	(3)	(4)
	g(Loans)			
Sovereigns$_{2010Q1}$	-0.169*	-0.416***	-0.593***	-0.107
	(0.098)	(0.122)	(0.169)	(0.139)
Interaction with:				
Low Capital Ratio$_{2010Q1}$	-0.439***			-0.293**
	(0.160)			(0.139)
Net Interbank Debt$_{2010Q1}$		-0.990***		-1.202**
		(0.274)		(0.474)
Deposits$_{2010Q1}$			0.202***	-0.160
			(0.065)	(0.123)
Firm Fixed Effect	Y	Y	Y	Y
Bank Controsl	Y	Y	Y	Y
Relationship Controls	Y	Y	Y	Y
Observations	478235	478235	478235	478235
R-squared	0.387	0.388	0.387	0.388

level: a financial intermediary that is close to the regulatory boundary tightens credit supply almost three times more than that experienced by more capitalized banks. This is a very large and significant effect. However, the funding structure seems to matter as well for determining the size of the effects. We find that banks that were more active in borrowing in the interbank market and that have a smaller deposit base experienced a much larger drop in lending. Comparing two banks experiencing the same shock but one standard deviation apart in interbanking borrowing, we found that the more active banks in the wholesale market would cut credit by one-third more than the less active banks. The horse-race specification (Column 4) confirms that both channels seem to be at work. In particular, while deposits loses statistical significance, we find that the coefficients associated with the capital measure and interbank market exposure are similar in both significance and magnitude.

Altogether, our analyses of the propagation channel of the sovereign shock to lending can be summarized in two findings. First, both the collateral channel and the funding channel appear to be economically relevant forces. The increase in sovereign risk affected credit both because it reduced the availability of the collateral needed to tap into interbank funding and because it raised concerns about the future funding conditions of poorly capitalized banks. This result is consistent with previous evidence ([190]; [204]), which highlights the importance of wholesale markets – and funding more generally – in explaining the effects of the sovereign crisis ([220]). It also confirms that banks' capital buffers shield borrowers from balance shocks that affect the value of intermediaries assets and (or) liabilities ([182]; [129]). Second, our analysis shows that, among the possible drivers of the funding channel, the main source of instability during this turbulent period was the reliance on wholesale funding rather than retail deposits. As in the case of the recent financial crisis ([191]; [47]), financial intermediaries' exposure to interbank markets appears to be a catalyst for the transmission of macro-financial shocks to the real economy.

3.5 Credit Supply and Corporate Behavior

The previous results confirm the presence of a sizable contraction in credit triggered by the turmoil in sovereign markets. In fact, we find that the shock to sovereign assets impaired the ability of banks to provide credit to firms. The next step is to evaluate whether this event had actual consequences on firms' behavior. Economic theory suggests that a tightening of credit supply can impair companies' ability to invest if they cannot compensate for the lower credit from exposed lenders with funding from other sources, either inside or outside the banking sector ([47]; [18]). Other studies have shown that a sudden reduction of credit availability also may affects borrowers' employment decisions ([45]; [17]). Our analysis confirms that financial frictions prevented firms from fully smoothing out the reduction in credit from intermediaries more exposed to the sovereign shock. Furthermore, we show that the credit contraction led to a reduction in firms' investment rates and employment, but only among small firms.[31]

In order to study how the the turmoil in sovereign markets affected firm activity, we examine whether a firm's exposure to the sovereign shock has any predictive power on changes in funding, investment, and employment decisions of the companies in our sample. We start by constructing a measure of firm-level exposure to the sovereign shock by computing the average exposure that firm j experiences through the connection with its lenders. Formally, let $\mathscr{B}_j$ be the set of all lenders to firm j in 2010:Q1. Then, we construct firm j's average exposure as:

$$\text{Sovereigns}^{AVE}_{j,2010Q1} = \sum_{b \in \mathscr{B}_j} \omega_{bj} \text{Sovereigns}_{b,2010Q1}$$

31. Even if the firms had been able to completely undo the bank-lending channel by borrowing from banks less exposed to the shock or resorting to other forms of financing, the sovereign crisis still could have propagated to the real economy through other channels. See, for example, [205] or [**?**].

where $\text{Sovereigns}_{b,2010Q1}$ is the stock of Italian sovereigns over RWA held by lender b in 2010:Q1.[32] Lender's exposures are *weighted* by the share of total bank credit the firm received from the bank before the Greek bailout (ω_{bj}). Using this measure, we study how different firm-level outcomes (y_j) are affected by the firm-specific exposure to the sovereign shock:

$$y_j = \alpha_0 + \alpha_1 \text{Sovereigns}^{AVE}_{j,2010Q1} + \Gamma \cdot X^{AVE}_{j,2010Q1} + \Lambda \cdot Z^{AVE}_{j,2010Q1} + \tau_{province} + \tau_{industry} + u_j \tag{3.2}$$

Mirroring the relationship-level analysis, we control for the weighted average of bank-specific ($X^{AVE}_{j,2010Q1}$) and relationship-specific variables described in Section 3.4.[33] Furthermore, $Z^{AVE}_{j,2010Q1}$ are firm-level controls: log revenues, log age, leverage, and credit score (Altman Z-score); $\tau_{province}$ and $\tau_{industry}$ are a set of province fixed effects and industry fixed effects (SIC 2-digits).[34] In line with previous literature (e.g., [44]), we cluster the standard errors at the level of the lead bank, which is the largest lender during the pre-bailout period.

The intuition behind this test is as follows. If the sovereign shock had no effect on firms' operations, then the lenders' exposure to sovereign securities should not predict any change

32. In our data set, on average, the exposure of firms to the sovereign crisis is 22 percent (mean of $\text{Sovereigns}^{AVE}_{j,2010Q1}$), with a standard deviation of 23 percent (standard deviation of $\text{Sovereigns}^{AVE}_{j,2010Q1}$).

33. The weighted averages of bank-specific and relationship-specific variables are constructed similar to $\text{Sovereigns}^{AVE}_{j,2010Q1}$. The only exception is the dummy for cooperative banks, which is equal to one if the major bank is a cooperative bank. For consistency, we define relationship-level controls –which similarly vary at bank level within a specific firms – as part of the set of bank controls.

34. The sample used is identical to the one used in the previous part of the paper, which is the sample of firms with loans reported in the Credit Register and for which firm-level information is available in CERVED. The usual filters are applied as described in Section (3.3). Furthermore, given the nature of the estimator, we require our firms to appear in the data both before and after the shock.

in outcomes ($\hat{\alpha}_1 = 0$). If instead relationship are sticky and difficult to build, the exposure of firms' lenders before the shock would still predict changes in y_j. For example, looking at change in total bank loan, an estimate $\hat{\alpha}_1$ significantly lower than zero would suggest that firms were unable to take actions that effectively neutralize the credit tightening by their current lenders.

Similarly to the within-firm model presented above, the identification of α_1 requires orthogonality between the banks' exposure to sovereign securities and firms' credit demand or investment opportunities. For instance, geographic or industry clustering might induce a sorting between banks more exposed to the sovereign shock and firms with worse investment opportunities. Unlike the first part of the paper, here we cannot directly control for unobservable demand-side shocks since we can only rely on between-firm variation.

We argue that Equation (3.2) can still provide reliable estimates of the causal effect of the sovereign shock on firm outcomes for three main reasons. First, our previous analysis has provided no evidence of a systematic sorting between highly exposed banks and firms whose credit demand is shrinking. In particular, we have shown that the loan-level estimates with and without the firm fixed effects are not statistically different, and therefore that the bias induced by demand is either nonexistent or relatively small (see Columns 1 and 2 in Table 2.2). Second, the industry and province fixed effects help directly address the correlated demand bias. Industry fixed effects control for the specialization of exposed lenders in industries suffering more severe contractions of economic activity. Province fixed effects control for the spatial clustering of banks and borrowers. If the sorting between banks and firms is caused by industry or geographical specialization in the banking sector, this set of fixed effects would be sufficient to address any concern related to the identification of α_1. Third, we augment our model with a set of firm-level controls measured before the shock: firm size, credit rating, age, and leverage. These controls absorb variation in the LHS not directly imputable to firms' exposure to the shock and, to the extent that they correlate with firms' unobservable changes in investment opportunities and credit demand, they help address the sorting bias discussed previously.[35] We provide further evidence against the presence of a bias in our results in the robustness section below.

Supply Shock and Access to Credit – The shock to sovereign holdings triggered a decline in credit supply via the bank lending channel. However, firms may have been able to limit the economic impact of the shock by borrowing from alternative, less exposed financial intermediaries. To investigate this issue, we estimate model (3.2) looking at the change in total bank loans. Our outcome variable is $g(\text{Loan}_j)$, which is the symmetric growth rate of bank credit one year before to one year after the Greek bailout.[36] In Table 2.6, we show that firms have been unable to fully undo the decline in credit from exposed borrowers, as the average exposure of their lenders at the onset of the sovereign shock is predictive of the change in total bank credit. This effect is both statistically and economically significant.

On average, one standard deviation increase in banks' holdings of Italian sovereign securities corresponds to a reduction of 5% in bank credit in the year following the burst of the sovereign crisis.

A number of frictions can explain why firms cannot fully undo the effects of the bank-lending channel. Economic theory suggests that the value of established credit relationships should be increasing in the degree of information asymmetry between firms and new financiers. Because transparency, amount of pledgeable collateral, and average monitoring costs fall with firm size, we expect small firms to be particularly vulnerable to balance sheet shocks that affect the credit supply of their existing lenders (e.g., [67]; [56]). To test this

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35. The estimates of a model without firms' controls are qualitatively identical. Results are available upon request.

36. For consistency with the first part of the paper, we calculate the growth rate as $g(\text{Loans}_j) = \frac{\text{Loans}_{j,Post} - \text{Loans}_{j,Pre}}{0.5 \cdot \left[\text{Loans}_{j,Post} + \text{Loans}_{j,Pre}\right]}$. In a previous version of the paper we constructed the growth rate as $\Delta \ln(\text{Tot Loans}_j)$, obtaining very similar results.

Table 2.6: Real effects of the sovereign crisis

This table examines the real effects of the sovereign shocks on firms' aggregate credit, employment, and investment. In Columns (1)-(3), the outcome variable is the normalized growth rate total bank loans granted to firm j before-to-after the onset of the sovereign crisis (g(Tot Loans)); In Columns (4)-(6) the outcome variable is the growth rate in firm's wage bill between 2009 and 2011 (gr(Empl)); In Columns (7)-(9) the outcome variable is the change in firm's fixed assets (tangibles and intangibles) between 2009 and 2011 (gr(Inv)). The main independent variables are the weighted average of the exposure to Italian sovereign scaled by RWA of firm j's lenders ($\text{Sovereigns}^{AVE}_{2010Q1}$) and its interactions with two proxies of firm size: the logarithm of firm's revenues and a dummy equal to one if firm j's revenue in 2009 is below the 2 million Euros (Small Firm_{2009}). All regressions include a set of weighted averaged bank-specific, a set of relationship-specific controls - all measured at the end 2010:Q1 -, and a set of firm-level controls measures in 2009. Small Firm_{2009} is also included in as a control in Column (3), (6), and (9). All regressions include province fixed effects and industry fixed effects, and they are estimated on the sample of firms with multiple credit relationships. Standard Errors are clustered at lead-bank level. *** denotes significance at the 1% level, ** at the 5%, and * at the 10%.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		g(Tot Loans)			gr(Empl)			gr(Inv)	
$\text{Sovereigns}^{AVE}_{2010Q1}$	-0.182***	-0.476***	-0.112*	-0.045	-0.431**	0.031	-0.038	-0.507***	0.059
	(0.057)	(0.183)	(0.059)	(0.040)	(0.192)	(0.047)	(0.038)	(0.143)	(0.068)
$\text{Sovereigns}^{AVE}_{2010Q1} \cdot \ln(\text{Revenues}_{2009})$		0.041*			0.054**			0.066***	
		(0.022)			(0.025)			(0.021)	
$\text{Sovereigns}^{AVE}_{2010Q1} \cdot \text{Small Firm}_{2009}$			-0.100*			-0.109***			-0.139**
			(0.057)			(0.042)			(0.064)
Industry and Province Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	141372	141372	141372	141372	141372	141372	141372	141372	141372
R-squared	0.111	0.111	0.112	0.026	0.026	0.026	0.012	0.012	0.012

hypothesis, we examine the heterogeneity of the treatment effect across firms of different sizes. We use two proxies of firm size: a continuous measure ($\text{Ln}(\text{Revenues}_{2009})$) and a discrete measure (Small Firm_{2009}). A firm is considered small if its revenues are below 2 million euros, which is a standard definition adopted by EuroStat.[37]

Table 2.6 shows that both large and small firms suffered from the credit contraction passed on by their lenders. However, the effect for small firms was significantly larger in magnitude. For any level of the shock, small firms suffered a reduction in credit which is almost twice as large as the effect for larger firms. The result is also confirmed by the continuous variable, and it is robust to the extra tests that we discuss later in the paper.

A natural question is whether the heterogeneous treatment effect is driven by a heterogeneous credit tightening or heterogeneous ability to react to a similar credit tightening. In other words, in order to claim that this result is due to the inability of smaller firms to counteract the credit tightening of existing lenders, we have to exclude the possibility that banks cut lending more aggressively to smaller firms in response to the sovereign shock. The within-firm regressions presented in the first part of the paper allow us to test this alternative hypothesis. We augment model (3.1) with an interaction between lenders' sovereign exposure and borrowers size. Table B.10 in the Appendix shows that banks did not cut more extensively smaller firms in our sample. The interaction between our treatment variable and size measures are both non significant and small in size relative to the main effect. This implies that the differential effect in credit contraction across large and small firms is driven by the relative inability of smaller businesses to smooth the credit shock across different lenders, rather than being the result of a larger credit tightening.

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37. See EuroStat for the definition of small firms based on revenues (http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32003H0361). Results are similar when using a dummy at the median of the distribution of the same variable.

While our results show that the tensions in sovereign markets significantly reduced the available credit to firms, these micro estimates are not directly informative of the aggregate effect of the shock on credit markets. To put our analysis into perspective, we use the results from the between-firm analysis (Table 2.6) to calculate the drop in aggregate credit due to the transmission of the sovereign shock via the bank-lending channel. For every firm j, we compute the percentage change in bank credit that can be imputed to its lenders' exposure to sovereigns. Then, we transform percentages into monetary amounts by multiplying them by the overall lending of firm j in the pre-period, and then use these quantities to calculate the aggregate drop in lending.[38] With respect to a counterfactual amount of credit constructed under the assumption that the sovereign shock had no effect on credit supply ($\hat{\alpha}_1 = 0$), we estimate that aggregate corporate lending dropped by 2% within a year following the Greek bailout due to the detrimental effect of distressed sovereigns on the balance sheets of financial institutions. This result confirms that the effects of a sovereign shock through a balance sheet channel were substantial also at aggregate level.

Real Effects on Investments and Employment – In this section we investigate wether the credit shock triggered by the burst of the sovereign crisis had any effect on investment and employment policies. On the one hand, firms facing credit tightening from lenders exposed to distressed securities may be able to substitute with financing from an alternative sources and undo the bank-lending-channel effects ([221]; [222]). On the other hand, credit market frictions may prevent credit-worthy borrowers in need of external financing from tapping into alternative sources of financing ([44]; [45]; [47]). In this case the drop in the availability of bank credit would impact firms' real activity and, thus, affect the economy as a whole.

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38. That is, we calculate the impact on each firm as $\hat{s}_j = ((\hat{\alpha}_1 \cdot \text{Sovereigns}^{AGE}_{j,2010Q1}) \cdot \text{Loans}_{j,PRE})$, and the aggregate impact on credit as $(\Sigma_j \hat{s}_j / \sum_j \text{Loans}_{j,PRE})$.

The key issue in the real-effects literature is the ability to disentangle credit constrained firms from firms with poor financial health or investment opportunities ([192]; [30]). To tackle this identification problem, we employ the specification in equation (3.2) and regress the sovereign exposure of a firm's lenders on changes in investments and employment. This approach has the advantage of allowing us to directly observe which firms experienced a restricted access to credit using lenders' health as a credit-supply shifter.

We measure investment dynamics looking at the growth rate of fixed assets between 2011 and 2009 (gr(Inv)). Ideally, we would want to replicate the same measure for employment, but information on the number of employees is available only for a small and selected sample of firms our dataset (approximately 15%). Instead, every firm reports full information on the wage bill paid during the fiscal year. Therefore, we study the effect of the sovereign shock on the labor market by looking at the growth rate of firms payroll (gr(Empl)) between 2009 and 2011 ([223]; [47]). Changes in this variable reflect a byproduct of adjustment in the number of employees, hours worked per employee, and wage per hour worked, and it has been generally considered a reliable measure of employment dynamics at the firm level.

We find that, on average, the credit shock had little or no effect on firms' real outcomes (Table 2.6). For investment, the coefficient associated with lenders' sovereign exposure is negative but nonsignificant at the canonical level, and economically small (Column 7). The same holds for employment (Column 4). The average effects, however, hide a substantial heterogeneity in the response across firms of different sizes. While we cannot reject the hypothesis that direct exposure to financial institutions to with higher holding of distressed securities had no effect on the real activity of largest firms, small firms' policies were deeply jeopardized by the balance sheet shock suffered by their lenders (Columns 8 and 9). For a small firm, an increase in exposure to sovereigns by one standard deviation translated into a 4% decline in investment. Moreover, lender health also had an economically and statistically significant effect on employment at small firms (Columns 5 and 6). A difference in one standard deviation in lenders' health leads to an average reduction in payments to labor of 3%.[39]

The micro estimates in Table 2.6 can also be used to back up the elasticities of investment and wage bills with respect to changes in credit supply. For a small change in lenders' sovereign exposure, we can express the average investment elasticity as the ratio between the average semi-elasticity of investment with respect to the supply shifter ($\frac{\partial gr(\text{Inv})}{\partial \text{Sov}^{AGE}_{j,2010Q1}}$) and the corresponding semi-elasticity of total bank credit ($\frac{\partial g(\text{Loan}_j)}{\partial \text{Sov}^{AGE}_{j,2010Q1}}$). The same approach can be used to examine employment. In line with the reduced-form analysis, the average elasticity for both asset and payroll is economically small (elasticity of 0.2). However, we find an economically significant sensitivity of both investment and payroll to changes in bank credit for small firms, but no sensitivity for larger firms.[40] In particular, we estimate a contraction by 38 cents of investments and 37 cents in payments to labor for every euro in funding. Relative to the most recent literature in this area, our results are larger than the estimates of [18] for investments, and somehow higher than the ones in [47] for both investments and payroll. This difference is not surprising, since the average firm in both studies is much bigger than the average firm in our sample of small firms, confirming that the sensitivity of corporate policies to bank credit is characterized by a substantial heterogeneity across firms of different size.

39. In principle, different theories can explain why a tightening of the credit supply had an effect on the labor policies of small enterprises. The availability of external financing may affect employment indirectly through its impact on firm level investment. The same credit-market frictions that curb investment and tie it to the availability of internal fund, lead firms to adjust employment due to the decline in capital. Moreover, when there is a mismatch between payments to labor and the ultimate generation of cash flow, firms will need to finance their labor activity throughout the production process. When the ability to finance working capital deteriorates, firm employment should fall.

40. For large firms, for which we found no effect of pre-shock lender's exposure on credit, the point estimates are negative but statistically highly non-significant.

Robustness Tests – We conclude this section with a set of robustness checks. With these tests we want to eliminate any remaining concerns that unobserved heterogeneity in investment opportunities or changes in credit demand – rather than shifts in credit supply – may be driving our findings on investment and employment policies.

First, we augment the model in (3.2) with the estimated firm fixed effects ($\hat{\rho}_j$) from the model in Equation (3.1) ([224]; [47]). Other studies employing a similar within-firm identification strategy have treated the estimated fixed effects as nuisance parameters ([**?**,47,130,132,225]). However, to the extent that this parameter proxies for real demand-side shocks, the estimated fixed effects may convey useful information on the transmission of the sovereign shock to the real economy. In Appendix B.7, we show that a more structural interpretation of parameter $\hat{\rho}_j$ seems reasonable. In fact, we find that $\hat{\rho}_j$ strongly correlates with a large set of variables that are generally considered to be correlated with credit demand in the literature in empirical corporate finance. As presented in Table 2.7, including the firm fixed effect from the within-firm regression as a control for credit demand does not affect our results, strengthening on confidence in the their causal interpretation. Importantly, this null result is not due to the lack of power of $\hat{\rho}_j$ in predicting firm behavior. Instead, we find that this alternative proxy of firms' credit demand is always highly significant and positive, and its inclusion explains a large share of the variation in the data.

Second, we show that adding more granular controls of local credit demand does not change our inference. In particular, we augment Equation (3.2) with an extra set of fixed effects at the province-by-industry level, which would effectively control for any unobservable variation in investment opportunities or credit demand that is specific to any industry-province pair. In other words, we compare two companies that are operating in the same industry and province but have different exposure to the sovereign shock. The only drawback of this approach is that our estimates would only reflect the set of observations for which we have variation in treatment within an industry-province pair. To make sure that

Table 2.7: Real effects of the sovereign crisis: Robustness with firm fixed effects

This table examines the real effects of the sovereign shocks on firms' aggregate credit, employment, and investment. It replicates Table 2.6 with additional controls for change in firm's credit demand. In Columns (1)-(3), the outcome variable is the normalized growth rate total bank loans granted to firm j before-to-after the onset of the sovereign crisis (g(Tot Loans)); In Columns (4)-(6) the outcome variable is the growth rate in firm's wage bill between 2009 and 2011 (gr(Empl)); In Columns (7)-(9) the outcome variable is the change in firm's fixed assets (tangibles and intangibles) between 2009 and 2011 (gr(Inv)). The main independent variables are the weighted average of the exposure to Italian sovereign scaled by RWA of firm j's lenders (Sovereigns$^{AVE}_{2010Q1}$) and its interactions with two proxies of firm size: the logarithm of firm's revenues and a dummy equal to one if firm j's revenue in 2009 is below the 2 million Euros (Small Firm$_{2009}$). In all regressions we control for the firm fixed-effect $\hat{\rho}_j$ estimated from the baseline regression of the bank lending channel (equation (3.1)). All regressions include a set of weighted averaged bank-specific, a set of relationship-specific controls - all measured at the end 2010:Q1 -, and a set of firm-level controls measures in 2009. Small Firm$_{2009}$ is also included in as a control in Column (3), (6), and (9). All regressions include province fixed effects and industry fixed effects, and they are estimated on the sample of firms with multiple credit relationships. Standard Errors are clustered at lead-bank level. *** denotes significance at the 1% level, ** at the 5%, and * at the 10%.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	g(Tot Loans)			gr(Empl)			gr(Inv)		
Sovereigns$^{AVE}_{2010Q1}$	-0.155***	-0.315***	-0.116***	-0.040	-0.401**	0.030	-0.031	-0.467***	0.058
	(0.027)	(0.104)	(0.031)	(0.040)	(0.200)	(0.045)	(0.038)	(0.145)	(0.063)
Sovereigns$^{AVE}_{2010Q1}$ · ln(Revenues$_{2009}$)		0.023*			0.051**			0.061***	
		(0.014)			(0.026)			(0.020)	
Sovereigns$^{AVE}_{2010Q1}$ · Small Firm$_{2009}$			-0.055*			-0.100**			-0.127**
			(0.030)			(0.042)			(0.062)
$\hat{\rho}$	0.833***	0.833***	0.833***	0.154***	0.154***	0.154***	0.207***	0.207***	0.207***
	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)
Industry and Province Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	141372	141372	141372	141372	141372	141372	141372	141372	141372
R-squared	0.688	0.688	0.688	0.041	0.041	0.042	0.028	0.028	0.028

this issue does not affect our results, we present the estimates interacting the province dummies with two different levels of industry aggregation. In particular, we look at both the two-digit or one-digit SIC codes.[41] Table 2.8 shows that results are generally unaffected by the inclusion of these more restrictive controls.

If anything, we find that the effect increases in magnitude, but the significance remains generally unchanged.[42] Furthermore, results are also not particularly different across the two specifications, showing that more or less restrictive fixed effects does not change our conclusions.[43]

In addition to firm size, the literature has provided other proxies of firms' sensitivity to the availability of external financing. To further explore the heterogeneous effects of a credit-supply shocks, we examine another measure – the level of dependence on external financing – to capture variation in the extent to which firm policies are responsive to credit tightening. In order to explore this aspect, we rely on underlying technological differences among industries and construct a measure of dependence on external finance following the classification proposed by [159].[44] We expect firms that are more heavily dependent on external financing to run their operations to be – all else equal – more affected by a credit

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41. When we use one-digit SIC interacted with province, we still leave the two-digit SIC codes not interacted as a baseline control, as presented in Equation (3.2).

42. The only exception is the column (3), where we study the interaction of the dummy measure of size with credit, using the most restrictive fixed effects. In this case, despite the coefficient being larger than in the baseline, it becomes weakly nonsignificant.

43. This positive result is somehow expected: Appendix **??** shows no evidence of overexposure of industries or geographical areas to financial institutions with sovereign holdings above the median.

44. More specifically, we use the Rajan-Zingales (RZ) index constructed using US Compustat firms, and we impute it to firms in our data set according to their industry. The intuition behind the RZ index is the following. For technological reasons some industries rely on external financing more than others. For example, some industries operate on a larger scale than others, have projects with longer gestation or require continuous investments to keep operating; thus, these industries should be more negatively affected than others by an unexpected tightening of credit supply. We refer to [159] for further details.

Table 2.8: Real effects of the sovereign crisis: Robustness with industry and province fixed effects

This table examines the real effects of the sovereign shocks on firms' aggregate credit, employment, and investment. It replicates Table 2.6 with additional controls for change in firm's credit demand. In Columns (1)-(3), the outcome variable is the normalized growth rate total bank loans granted to firm j before-to-after the onset of the sovereign crisis (g(Tot Loans)); In Columns (4)-(6) the outcome variable is the growth rate in firm's wage bill between 2009 and 2011 (gr(Empl)); In Columns (7)-(9) the outcome variable is the change in firm's fixed assets (tangibles and intangibles) between 2009 and 2011 (gr(Inv)). The main independent variables are the weighted average of the exposure to Italian sovereign scaled by RWA of firm j's lenders (Sovereigns$^{AVE}_{2010Q1}$) and its interactions with two proxies of firm size: the logarithm of firm's revenues and a dummy equal to one if firm j's revenue in 2009 is below the 2 million Euros (Small Firm$_{2009}$). All regressions include a set of weighted averaged bank-specific, a set of relationship-specific controls - all measured at the end 2010:Q1 -, and a set of firm-level controls measures in 2009. Small Firm$_{2009}$ is also included in as a control in Column (3), (6), and (9). Regressions in Panel a includes province fixed effects, industry fixed effects (2 digits), and macro-industry (1 digit) by province fixed effects. Regressions in Panel b include province (2 digits) by industry fixed effects. All regressions are estimated on the sample of firms with multiple credit relationships. Standard Errors are clustered at lead-bank level. *** denotes significance at the 1% level, ** at the 5%, and * at the 10%.

Panel a: Province by macro-industry (1 digit) fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		g(Tot Loans)			gr(Empl)			gr(Inv)	
Sovereigns$^{AVE}_{2010Q1}$	-0.186***	-0.492***	-0.113*	-0.037	-0.039	-0.406**	0.027	-0.542***	0.058
	(0.055)	(0.179)	(0.059)	(0.041)	(0.038)	(0.203)	(0.048)	(0.148)	(0.069)
Sovereigns$^{AVE}_{2010Q1}$ · ln(Revenues$_{2009}$)		0.043**			0.051**			0.071***	
		(0.022)			(0.026)			(0.021)	
Sovereigns$^{AVE}_{2010Q1}$ · Small Firm$_{2009}$			-0.107*			-0.100**			-0.141**
			(0.059)			(0.042)			(0.068)
Industry and Province Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Macro Industry x Province Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	141372	141372	141372	141372	141372	141372	141372	141372	141372
R-squared	0.118	0.118	0.118	0.035	0.017	0.035	0.035	0.017	0.017

Table 2.8 (cont'ed): Real effects of sovereign shock: Robustness with industry and province fixed effects

Panel b: Province by industry fixed effects (2 digits)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	g(Tot Loans)			gr(Empl)			gr(Inv)		
$\text{Sovereigns}^{AVE}_{2010Q1}$	-0.167***	-0.448**	-0.107*	-0.037	-0.060	-0.346*	0.034	-0.549***	0.049
	(0.057)	(0.179)	(0.059)	(0.039)	(0.038)	(0.191)	(0.046)	(0.145)	(0.067)
$\text{Sovereigns}^{AVE}_{2010Q1} \cdot \ln(\text{Revenues}_{2009})$		0.039*			0.051**			0.069***	
		(0.022)			(0.026)			(0.021)	
$\text{Sovereigns}^{AVE}_{2010Q1} \cdot \text{Small Firm}_{2009}$			-0.087			-0.100**			-0.158**
			(0.057)			(0.042)			(0.066)
Industry x Province Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	141372	141372	141372	141372	141372	141372	141372	141372	141372
R-squared	0.144	0.144	0.145	0.064	0.041	0.064	0.064	0.041	0.041

shock. The results reported in Table B.12 in the Appendix B.8 are in line with this hypothesis. We find that firms that are more dependent on external financing cut employment relatively more than other firms in response to the sovereign shock. The same does not hold for investment, for which we cannot find any statistically significant effect. These findings are in line with those in [208], which showed that dependence on external financing had a particularly strong role in explaining the firms' employment cuts during the recent financial crisis in the US. Importantly, we find that credit does not decline relatively more (or less) for more externally dependent firms. This reassuring, since we did not expect a different degree of dependence on external financing to play an unambiguous role in determining firms' ability to smooth the credit shock across lenders once firm characteristics are controlled for.

Altogether, our results suggest that the credit tightening caused by the sovereign crisis had sizable impact on the real economic, with a disproportional effect on small companies that experienced a significant drop in both bank credit, investment and employment. Importantly, we have shown that credit supply shocks are particularly disruptive for small businesses, even when credit markets do not discriminate against them. As discussed in Section 3.4, in our setting banks did not cut credit more extensively to smaller companies. Instead, the disproportional effect on small-firm activity seems to be explained by their greater sensitivity to the availability of credit provided by their existing lenders. Compared to larger firms, small firms appear to be less able to compensate for a credit shortage of equal magnitude across different lenders ([44]; [45]). Furthermore, small businesses have less funding opportunities outside bank credit, and therefore they tend to be more sensitive to the state of the capital market as a whole.

3.6 Conclusions

Using a detailed firm–bank panel data set extracted from the Italian Credit Registry, we document the propagation of sovereign tensions spurred by the Greek bailout to the real economy through a deterioration of banks' balance sheets. Tensions in the sovereign market led to a tightening in credit supplied by financial institutions more exposed to sovereign securities of distressed countries and a consequent reduction in investment and employment by small firms that relied on the financing provided by these banks. At the firm level, when comparing lending to the same firm by two banks one standard deviation apart in sovereign holdings, the more exposed bank reduced loan supply by 10% more than the other in the year after the Greek bailout. At the aggregate level, our calculations reveal that the sovereign shock passed along through bank exposure can account for about 2% of the reduction of corporate lending over the same period.

Our results confirm that the security portfolio of banks can be the vehicle through which international macro-shocks can be propagated to the domestic economy. More broadly, we show that banks were unable to shield the real economy from fluctuations in value of their non-loan portfolios; and that the fragility of intermediaries' balance sheets amplified the effects of financial market fluctuations. Therefore, our paper provides novel evidence on the important role played by the banking system in the context of financial contagion across countries (e.g., [129,181,193,194]). Since sovereign bonds are among the least volatile asset classes in the portfolio of financial intermediaries, we think of our estimates as a lower bound for the real economic costs due to the security channel.

These results are also relevant to understand the role of sovereign in banks' balance sheet. Government bonds are typically viewed as a safer asset relative to other securities. However, a large and concentrated exposure to this asset class may still lead to a sizable contraction in credit during turmoil in sovereign debt markets ([226]). The risks associated with a financial system encumbered by an undiversified stock of public debt are still very concerning today, since financial institutions increased their exposure to sovereign securities issued by their own governments as a result of the recent European crisis ([199]; [183]). This fact is true for several countries around the world, and at different levels of economic development.

Furthermore, the granularity of our data and the quality of our setting allows us to provide new evidence on the importance of bank credit for small firms. A series of papers have highlighted the need to break down the effects of the bank-lending channel by firm size ([67]; [44]; [45]). Our study takes on this challenge and overcomes the data constraints that have limited past analyses to larger and more transparent firms. We show that, even if small companies were not a direct target of bank credit tightening, the real economic costs of financial instability could be particularly high for them. This implies a large elasticity of real activity to credit for small firms. Any policy intervention that aims to reduce the impact of credit shocks on the real economy must internalize this heterogeneity.

APPENDIX B

B.1 Data selection and other information on data construction

In this section, we discuss the data construction process. Starting from the universe of all business credit relationships appearing in the Italian Credit Register, we classify firms into two groups. The first sub-sample includes a random sample of seventy percent of all borrowers which established credit relationships with only one lender during our pre-shock period (2009:Q2-2010:Q1). The second group includes every firms which established multiple, simultaneous lending relationships with several banks.

For each of these two sub-samples, we exclude a number of observations. We drop defaulted loans as well as new credit granted to borrowers who already have some other relations in default, as these positions may no longer reflect genuine demand and supply dynamics, but rather capture debt restructuring operations or some other agreement due to the default procedures. We drop observations for which we have no information about the lender. We excludes credit provided by special purpose vehicles, non-bank financial intermediaries, and branches of foreign banks for which we have no detailed balance sheet information.[45] We drop observations referring to borrowers which operate in the financial and insurance sector, utilities and government-related industries. We exclude firms operating in the education sector and utilities because, for a majority of the cases, the government either runs them directly or indirectly subsidizes their activity. We eliminate firms with more than seven contemporaneous credit relationship, i.e. firms belonging to the top 5% of the distribution of lending relationships.[46]

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45. As explained in [47], these lenders grant only a small share of total loans to Italian firms (about 6 percent).

46. Our inspection of the data suggest that some of the credit relationships of firms with a high number of lending relationships do not reflect genuine credit relationships.

Table B.1: Distribution of firms across geographical regions

This table reports the distribution of firms across the Italian regions. The sample includes firms which established multiple lending relationships, after the application of the filters described in Appendix B.1. The first column reports the industry composition of the whole sample. The second and third column report the industry composition within the sub-samples of firms borrowing from banks with sovereigns exposure ($\text{Sovereigns}^{AVE}_{j,2010Q1}$) above the median and below the median, respectively. Source: Italian Credit Register, Bank of Italy.

Region	Whole Sample (%)	Low Sovereigns (%)	High Sovereigns (%)
1	0.02	0.01	0.01
2	0.01	0.00	0.00
3	0.01	0.01	0.00
4	0.05	0.03	0.02
5	0.11	0.04	0.07
6	0.02	0.01	0.01
7	0.08	0.04	0.04
8	0.02	0.01	0.01
9	0.25	0.12	0.13
10	0.03	0.02	0.02
11	0.00	0.00	0.00
12	0.07	0.03	0.04
13	0.04	0.02	0.02
14	0.02	0.01	0.01
15	0.04	0.02	0.02
16	0.08	0.06	0.02
17	0.02	0.01	0.01
18	0.02	0.01	0.01
19	0.00	0.00	0.00
20	0.12	0.05	0.07

B.2 Variables description

Relationship-specific variables – Our main dependent variable is the percentage change in average outstanding loans between the pre- and post-shock period for every firm-bank

Table B.2: Distribution of firms across industries

This table reports the distribution of firms across different macro industries. Macro industries are defined as broad aggregates of SIC codes. The sample includes firms which established multiple lending relationships, after the application of the filters described in Appendix B.1. The first column reports the industry composition of the whole sample. The second and third column report the industry composition within the sub-samples of firms borrowing from banks with sovereigns exposure ($Sovereigns^{AVE}_{j,2010Q1}$) above the median and below the median, respectively. Source: Italian Credit Register, Bank of Italy.

Industry	Whole Sample (%)	Low Sovereigns (%)	High Sovereigns (%)
AGRICULTURE, FORESTRY AND FISHING	0.02	0.01	0.01
MINING AND QUARRYING	0.00	0.00	0.00
MANUFACTURING	0.34	0.17	0.17
CONSTRUCTION	0.14	0.07	0.07
WHOLESALE AND RETAIL TRADE; REPAIR OF VEHICLES	0.26	0.13	0.13
TRANSPORTATION AND STORAGE	0.04	0.02	0.02
ACCOMMODATION AND FOOD SERVICE ACTIVITIES	0.04	0.02	0.02
INFORMATION AND COMMUNICATION	0.04	0.02	0.02
REAL ESTATE ACTIVITIES	0.01	0.01	0.01
PROFESSIONAL, SCIENTIFIC AND TECHNICAL ACTIVITIES	0.05	0.02	0.03
ADMINISTRATIVE AND SUPPORT SERVICE ACTIVITIES	0.03	0.01	0.02
ARTS, ENTERTAINMENT AND RECREATION	0.02	0.01	0.01

Table B.3: Summary statistics: multiple and one lending relationships firms

This table reports the summary statistics of the relationship-specific (panel a) and firm-specific (panel b) for the full sample of firms that established at least one lending relationship in the one-year window centered around the Greek bailout.

Panel a: Relationship-specific Variables

Variable	Obs	Mean	Sd	Sd (within)	Sd (Between)	Pc10	Pc90
g(Loans)	533904	0.020	0.647	0.497	0.452	-0.549	0.667
g(Tot Credit)	533904	0.029	0.592	0.430	0.462	-0.462	0.667
g(Cred Lines)	533904	0.007	0.627	0.461	0.492	-0.545	0.667
1(Cut Credit)	533904	0.386	0.487	0.366	0.368	0.000	1.000
Δ ln(Loans)	533904	0.020	0.552	0.353	0.508	-0.494	0.659
Length Relationship$_{2010Q1}$	533904	27.897	22.214	16.317	19.075	1.000	60.625
Share Relationship$_{2010Q1}$	533904	9.783	5.693	3.591	4.554	2.000	17.000
Num Relationship$_{2010Q1}$	533904	3.437	1.670	0.000	1.508	1.000	6.000

Panel b: Firm-specific Variables

Variable	Firms	Mean	Sd	Pc10	Pc90
Assets$_{2009}$	185133	5113.783	53657.700	285.000	7871.000
Revenues$_{2009}$	185133	4684.015	41944.453	275.000	7421.000
Wage Bill$_{2009}$	185133	719.486	5441.718	40.000	1183.000
Age$_{2009}$	185133	15	12	3	31
Bank Leverage$_{2009}$	185133	36.746	27.087	6.673	73.331
Credit Score$_{2009}$	185133	5.073	3.828	2.000	7.000
gr(Empl)	185133	0.035	0.507	-0.432	0.486
gr(Inv)	185133	-0.014	0.650	-0.665	0.693

credit relation in our data set. More precisely, we collapse the quarterly amount of credit granted to firm j by bank b to two a pre-shock average (2009:Q2-2010:Q1) and the post-shock average (2010:Q2-2011:Q1). Collapsing the dataset into a pre-shock and post-shock average reduces concerns related to serial correlation of the errors ([217]) and to average out any seasonality ([**?**]). Then, we calculate the standardized growth rate between the two averages ([**?**]; [**?**]):

$$g(\text{Loans}_{bj}) = \frac{\text{Loans}_{bj,Post} - \text{Loans}_{bj,Pre}}{0.5 \cdot \left[\text{Loans}_{bj,Post} + \text{Loans}_{bj,Pre}\right]}$$

this growth rate is a second-order approximation of the log difference growth rate around 0; it is bounded in the range [–2,2], limiting the influence of outliers; and it accounts for changes in credit along both the intensive and extensive margin. We also construct a growth rate that considers only the change along the intensive margin ($\Delta ln(\text{Loans}_{bj})$, and a dummy variable that flags those relationship in place before the Greek bailout but terminated afterwards (Cut Credit_{bj}). In general, we show that our results are not affected by the choice of the outcome variable.

Bank-specific variables – All bank-specific variables come from the Bank of Italy Supervisory Records, and they are measured at the end of 2010:Q1 (the quarter before the sovereign shock). These variables include the stock of Italian sovereigns over risk-weighted assets ($\text{Sovereigns}_{2010Q1}$), the stock of Italian sovereigns over Tier1 ($\text{Sovereigns/Tier1}_{2010Q1}$), , the stock of Italian sovereigns over total assets ($\text{Sovereigns/Assets}_{2010Q1}$), the faction of total sovereign portfolio invested in Italian government bonds ($\text{Sovereigns}_{2010Q1}$ over Total $\text{Sovereigns}_{2010Q1}$), profitability ($\text{ROA}_{2010Q1}$), bank size ($\text{Size}_{2010Q1}$, expressed as a log-transformation), Tier1 ratio (Tier1_{2010Q1} over RWA), deposits ratio (Deposits_{2010Q1} over RWA), liquidity ratio ($\text{Liquidity}_{2010Q1}$ over RWA), (net) interbank market ratio (Net Interbank Debt_{2010Q1} over RWA), quality of lending portfolio (Bad Loans_{2010Q1}over RWA), an indicator variable for cooperative banks (BCC), total stock sovereign securities over RWA (Total Sovereigns$_{2010Q1}$), total stock sovereign securities issued by GIPSI (GR,IR,PR,SP, and IT) over RWA (Total Sovereigns GIPSI$_{2010Q1}$), and total stock of sovereign securities issued by GIPS (GIPSI less IT) over RWA (Total Sovereigns GIPS$_{2010Q1}$); a dummy indicating Tier1 ratio < 10% (Low Capital Ratio$_{2010Q1}$ over RWA). Furthermore, we also use two variables capturing the strength of the relationship between firm j and bank b. These are Lenght Relatioship$_{2010Q1}$, which indicates the length of the lending relationship (in quarters) between borrower j and bank b, measured as the number of quarters the relationship has been in place between 2006:Q1 and 2010:Q1; Share Relatioship$_{2010Q1}$ is the faction of borrower j total bank credit provided by the lender b, at the quarter right before the crisis.

Firm-specific variables – All firm-specific variables come from the CERVED database. Total assets$_{2009}$ (thousand euros), Revenues$_{2009}$ (thousand euros) refer to fiscal year 2009. We measure investment as the log change in fixed assets (both tangible and intangible) between 2009 and 2011 (gr(Inv)), and change in employment as the log change in wage bill (gr(Empl)). To limit the influence of outliers in the growth rate of investment and employment we winsorize the top and bottom 1% of the distribution of these variables. We use two alternative definitions of small firms: log Revenues$_{2009}$ and a dummy variable that flags firms below 2 million euros in accordance to the definition of EuroStat. Our definition of industry follows the Nace Rev. 2 classification. Through the paper we use a two-digit classification. In Table 2.8 we also use one-digit industries by province, but only when interacted with province.

Furthermore, our analysis in the second part includes province fixed effects. At the time of our analysis, there were 110 provinces in Italy, which can be roughly compared to US counties. As pointed out by [**?**], provinces represent a proper boundaries of the local market for bank credit. Indeed, provinces have been historically used by Bank of Italy to decide opening of new branches, and by the antitrust authority to assess and regulate deposit market concentration. Credit Rating$_{2009}$ is the credit score of the firm measured as the Altman Z-score ([69]; [70]). Age is measures in years between year of incorporation and 2009. Leverage is measured as the ratio between firm's bank credit (from the Credit Registry) and firm's total assets, both measured at the end of 2009. RZ Index is the [159] index of dependence on external finance. Following [159], we construct the RZ index for each industry (SIC 2-digits) as the median of (CapEx - Cash from Operations)/CapEx, using data from the firms in Compustat North America between 1980 and 2008.

B.3 Sovereign Holdings and Banks: A Cross-Country Comparison

Focusing on Italy, we are able to exploit the Italian Credit Register data and therefore we can provide a very detailed and precise account of the effects of sovereign holdings during a period of macroeconomic distress. However, this choice may generate concerns regarding the external validity of our results. First, it is important to highlight that regulation is relatively homogeneous across other developed countries, in particular within Europe. However, to address further concerns, in this section we show that both the characteristics of the banking sector and its exposure to sovereign risk are not substantially different to other Western countries.

We collect data on annual balance sheet and income statement information of banks operating in a large number of countries from Bankscope.[47] We focus on the sub-sample of banks that are active in Europe and United States, and compared them to Italian banks

47. Bankscope is a database managed by Bureau van Dijk Electronic Publishing (BvD). This data has been used in other works and its quality has been also recently scrutinized by [**?**].

along a number of dimensions. The summary statistics per country are available in Table B.4. All data refer to fiscal year 2009, the last one available before the Greek bailout.

A cross-country comparison of capital structure across the financial institutions in our sample (Panel (b)) displays that Italian banks are comparable to other intermediaries in terms of capitalization and maturity of liabilities, especially intermediaries from other European countries. This is not surprising given the emphasis placed on capital requirements by the Basel regulation and the similarities in regulations across Western countries. With the exception of German and British banks, equity is typically around 12-14 percent of total liabilities. The average bank in Italy, France, Ireland and the Netherlands appears to have ample reliance on long-term funding, coherently with the business model prevailing in Europe. In particular, Italian banks have one of the largest share of assets funded by long-term debt, which should make the banking sector overall more resilient to a crisis episode. Furthermore, loans represent a slightly larger share of asset for Italian banks relative to other European countries, but this number is still similar to US banks. At the same time, we do not observe significant differences between Italian banks and the rest of the sample in terms of net income and impaired loans.

Most importantly, Italian banks are not unique in terms of their exposure to sovereign securities. According to Bankscope, Italian banks hold around 14 percent of asset in government issued bonds. While this number is on the upper tail of the distribution of government bond holdings in our sample, in every country banks tend to be very exposed to sovereign securities. In fact, excluding Italy, the average portion of total assets invested in sovereign securities is about 8 percent for the banks in our sample, with Netherlands, Ireland and Greece having around 10 percent of their assets held in government debt.[48]

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48. For the USA, the variable total government assets is comparable to the variable Treasure and Agency Securities from the Flow of Funds data.

Bankscope does not provide the share of the total sovereign assets that are issued by the bank's own government. This information is instead provided by [**?**], who collected data on the share of total public debt that is held by domestic banks for a sample Western countries. In Figure B.3, we report the share of national debt held by resident financial institutions at the end of calendar years 2008 to 2011. According to these estimates, Italian banks hold 12 percent of outstanding national debt at the end of 2008, and gradually increased their holdings in the following three years, reaching 16.5 percent at the end of 2011. These percentages are not very different from other countries in the euro area - such as France, Ireland and Greece (before 2011). Italian banks hold more debt issued by their own government than intermediaries in the UK, the US and the Netherlands. On the contrary, banks from Belgium, Spain, Portugal and Germany are more exposed to national sovereign debt than Italian intermediaries. Indeed, if we rank these countries according to the percentage of national debt held by domestic banks, the Italian banking system positions itself in the middle of the distribution.

This descriptive evidence suggests that the Italian banking system shows no anomalies when compared to that of other developed counties, both in terms of profitability and capital structure. On average, Italian banks have a higher fraction of assets represented by sovereign bonds, but this investment strategy is common to other Western countries as well.

B.4 Correlation Between Greek and Italian Sovereign Yields

We focus our analysis around the Greek bailout in April 2010. As discussed in the paper, this timing is justified by at least two considerations: (i) The Greek bailout led to an unexpected shock to sovereign holdings, which was orthogonal to the sovereign holding or

Table B.4: International comparison of banking systems

This table presents a sequence of descriptive statistics describing the financial system of 11 countries: Italy (IT), Germany DE), France (FR), Belgium (BE), Netherlands (NL), United Kingdom (UK), United States (US), Greece (GR), Ireland (IR), Portugal (PT) and Spain (ES). Panel a refers to the asset structure, while Panel b focuses on the capital structure of the financial intermediaries operating in each country. All variables are measured at the end of fiscal year 2009. We presents the average and standard deviation (in parenthesis) of the variables of interest across all banks operating in each country. Government bonds are reported at book value. Source: Bankscope.

Panel a: Asset Structure

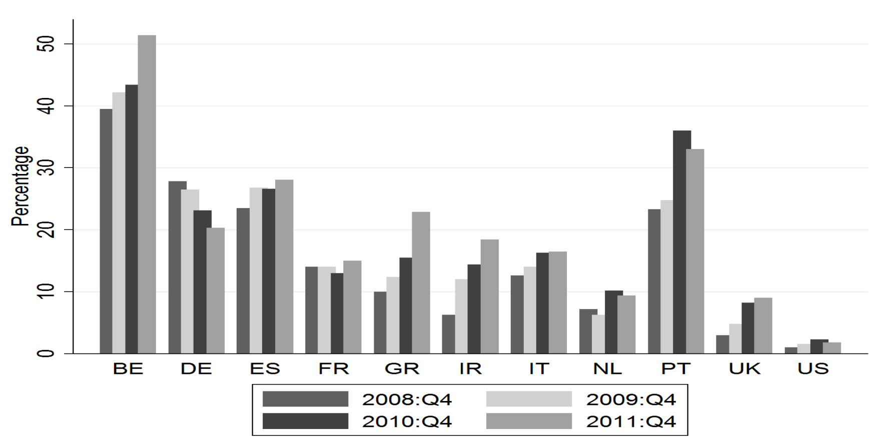
	BE	DE	ES	FR	GR	IR	IT	NL	PT	UK	US
Tot. Sovereign Securities / Tot. Assets	0.18	0.02	0.05	0.06	0.09	0.1	0.14	0.09	0.04	0.07	0.1
	(0.23)	(0.04)	(0.05)	(0.11)	(0.09	(0.21)	(0.11)	(0.08)	(0.06)	(0.09)	(0.11)
Tot. Loans / Tot. Assets	0.42	0.54	0.63	0.58	0.67	0.42	0.66	0.57	0.55	0.45	0.63
	(0.28)	(0.16)	(0.23)	(0.27)	(0.13	(0.31)	(0.19)	(0.25)	(0.27)	(0.28)	(0.17)
Return on Avg. Asset	0.71	0.26	0.36	0.95	-0.13	-1.11	0.38	1.29	0.34	0.08	-0.09
	(2.65)	(0.39)	(0.97)	(3.54)	(1.15	(4.07)	(0.79)	(4.09)	(1.56)	(7.38)	(1.94)
Return on Avg. Equity	6.18	3.86	2.89	5.34	-5.52	-20.01	3.59	4.44	4.78	1.1	-2.33
	(13.53)	(4.8)	(16.9)	(15.48)	(20.68	(61.86)	(6.78)	(14.5)	(10.96)	(32.9)	(24.35)
Net Income / Tot. Assets	0.01	0	0	0.01	0	-0.01	0	0.01	0	-0.14	0
	(0.03)	(0.01)	(0.02)	(0.05)	(0.01	(0.05)	(0.01)	(0.04)	(0.01)	(2.58)	(0.03)
Impaired Loans / Tot. Assets	0.01	0.04	0.03	0.03	0.07	0.05	0.05	0.02	0.04	0.03	0.03
	(0.01)	(0.03)	(0.02)	(0.04)	(0.06)	(0.07)	(0.04)	(0.01)	(0.05)	(0.06)	(0.03)

Panel b: Liability Structure

	BE	DE	ES	FR	GR	IR	IT	NL	PT	UK	US
Equity / Tot. Assets	0.18	0.08	0.12	0.14	0.12	0.08	0.12	0.16	0.14	0.22	0.11
	(0.23)	(0.04)	(0.05)	(0.11)	(0.09)	(0.21)	(0.11)	(0.08)	(0.06)	(0.09)	(0.11)
Long-term Debt / Tot. Assets	0.11	0.04	0.2	0.17	0.06	0.21	0.3	.19	0.2	0.11	0.05
	(0.14)	(0.07)	(0.18)	(0.8)	(0.04)	(0.27)	(0.14)	(0.21)	(0.17)	(0.19)	(0.1)
(Deposits + Short Term Debt) / Tot. Assets	0.69	0.86	0.78	0.72	0.8	0.61	0.56	0.76	0.64	0.69	0.82
	(0.27)	(0.12)	(0.17)	(0.26)	(0.16)	(0.28)	(0.14)	(1.12)	(0.23)	(0.29)	(0.15)
Tier 1 Ratio	12.99	10.83	10.28	12.39	15.23	12.25	16.14	15.28	12.59	15.22	14.95
	(3.21)	(3.57)	(5.67)	(5.69)	(10.27)	(6.47)	(8.68)	(11.24)	(6.94)	(9.53)	(10.27)

Figure B.1. Holding of domestic sovereign by domestic banks

This graph reports share of domestic public debt held by domestic financial institutions for a selected sample of countries, across different years. Source: data from [?].



lending behavior of Italian banks at that time; (ii) The Greek bailout led to an unprecedented change in sovereign markets. As we discuss in Section (3.2), many papers share this view and provide evidence in line with these statements.

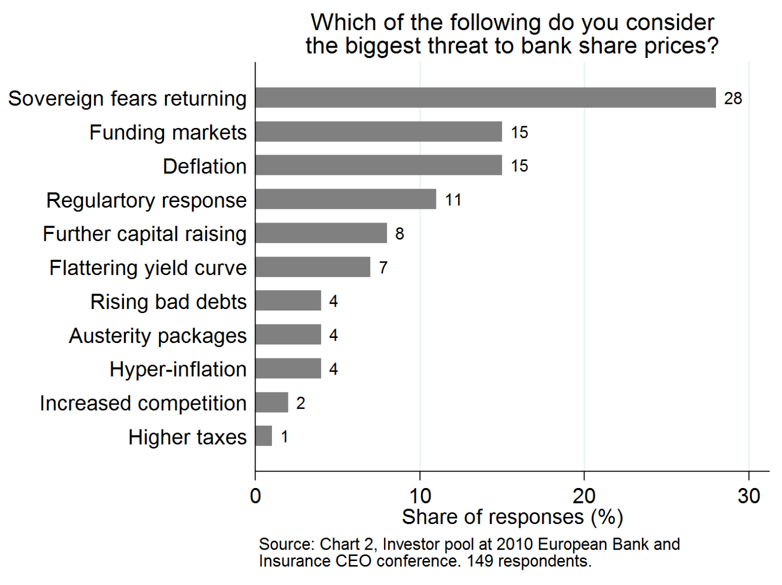
We provide more evidence in line with these hypotheses by studying the correlation between the spread of Italy and Greece between 2006 and 2012 (Table B.4). In particular, we focus our analysis in four periods. First, until the beginning of 2009, the two spreads were very small, and they strongly co-moved together. This pattern changes when, in the fall of 2009, the news regarding the fiscal misconducts of Greece starts to become public. While the Greek spread started to increase, the Italian one remained stable. As a consequence, the correlation during this window is much lower and not significantly different from zero.[49] However, in the second quarter of 2010, when the shock to sovereign risk was transmitted to other European countries, among which also Italy, the correlation increased again, remaining at this high level thereafter.

49. The correlation becomes negative if we restrict the window to consider only the months since the summer.

Figure B.2. Investors pool: European bank and insurance CEO conference

These two Figures report the results of a survey of investors conducted during the European Bank and Insurance CEO conference organized in September 2010 in London by Bank of America Merrill Lynch. Source: investor poll conducted during the European Bank and Insurance CEO. Charts available at http://ftalphaville.ft.com/2010/10/04/359726/european-bank-watch-past-present-and-future/.

Panel a: Threat to bank's share prices



Panel b: Expected performance of financial institutions

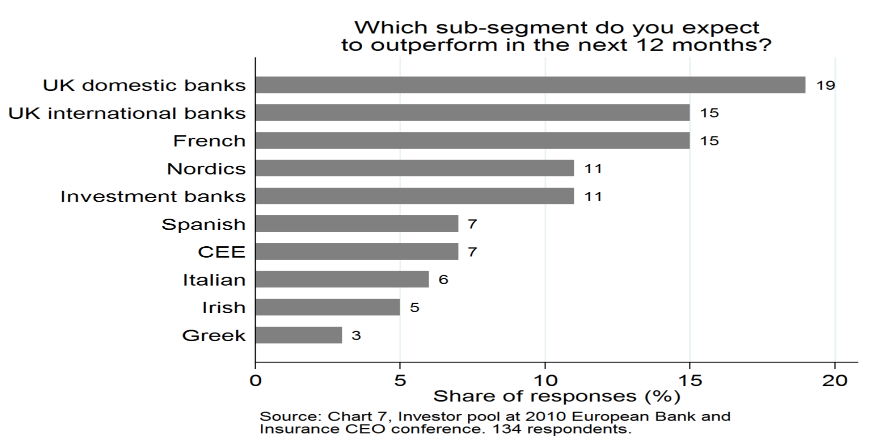


Table B.5: Correlation between the Italian and Greek spread

This table reports the the correlation between the Italian and Greek spread over German bonds, calculate for four different temporal windows. We use monthly yields on zero coupon bonds with 10 yeas maturity. Data are publicly available on the ECB web page. *** denotes significance at the 1% level, ** at the 5%, and * at the 10%.

Period	2006-2009Q1	2009Q2-2010Q1	2010Q2-2011Q1	2011Q2-2012
$\hat{\rho}$	0.984***	0.264	0.778***	0.641***
(p-value)	0.000	0.361	0.002	0.002

B.5 Bank Characteristics and Sovereign holding

Table B.6: Banks characteristics and sovereign holdings

This table shows the relation between intermediaries' exposure to the sovereign crisis (fraction of bank's RWA invested in Italian sovereign securities, $\text{Sovereigns}_{2010Q1}$) and a host of bank-specific characteristics: profitability, size, capitalization, deposits ratio, liquidity ratio, interbank market participation, quality of lending portfolio, and status of the bank as a cooperative bank. All variables are measured at the end 2010:Q1. The first and second column report, respectively, the mean and standard deviation (in parenthesis) of bank's characteristics sorting bank into two groups: above and below the median exposure. The third column shows the difference between the first and the second column and the standard errors of a two-sample t-test of the equality of the means (in parenthesis). The fourth column shows the pairwise correlation between $\text{Sovereigns}_{2010Q1}$ and banks characteristics and the p-value of this correlation (in parenthesis). *** denotes significance at the 1% level, ** at the 5%, and * at the 10%.

	Below Median of $\text{Sovereigns}_{2010Q1}$	Above Median of $\text{Sovereigns}_{2010Q1}$	Difference Below-Above	Correlation with $\text{Sovereigns}_{2010Q1}$
ROA_{2010Q1}	0.00	0.00	-0.00	0.04
	(0.00)	(0.00)	(0.00)	(0.36)
Size_{2010Q1}	6.19	5.03	1.16***	-0.26***
	(1.77)	(1.24)	(0.13)	(0.00)
Tier1_{2010Q1}	0.14	0.20	-0.06***	0.45***
	(0.12)	(0.16)	(0.01)	(0.00)
Deposits_{2010Q1}	0.61	0.99	-0.37***	0.75***
	(0.32)	(0.51)	(0.04)	(0.00)
$\text{Liquidity}_{2010Q1}$	0.00	0.01	-0.00***	0.26***
	(0.00)	(0.01)	(0.00)	(0.00)
Net Interbank Debt_{2010Q1}	-0.06	-0.11	0.05**	-0.11***
	(0.33)	(0.15)	(0.02)	(0.01)
Bad Loans_{2010Q1}	0.03	0.05	-.010***	0.1052**
	(0.03)	(0.04)	(0.00)	(0.01)
BCC	0.61	0.88	-0.27***	0.09***
	(0.48)	(0.32)	(0.03)	(0.04)

B.6 Semi-parametric estimation of the bank lending channel

This Section provides more details on the semi-parametric tests presented in Figures 3.1 of Section 3.4. Furthermore, we provide a robustness to that result, using a slightly modified method in Figure B.3.

We start by sorting banks into *"High Sovereign"* group (our "treatment group") and a *"Low Sovereign"* group (our "control group") based their (conditional) holding of Italian sovereigns in the last quarter before the shock. To do so, we run a cross-sectional of $\text{Sovereigns}_{b,2010Q1}$ on a battery of bank-level characteristics and balance sheet variables:

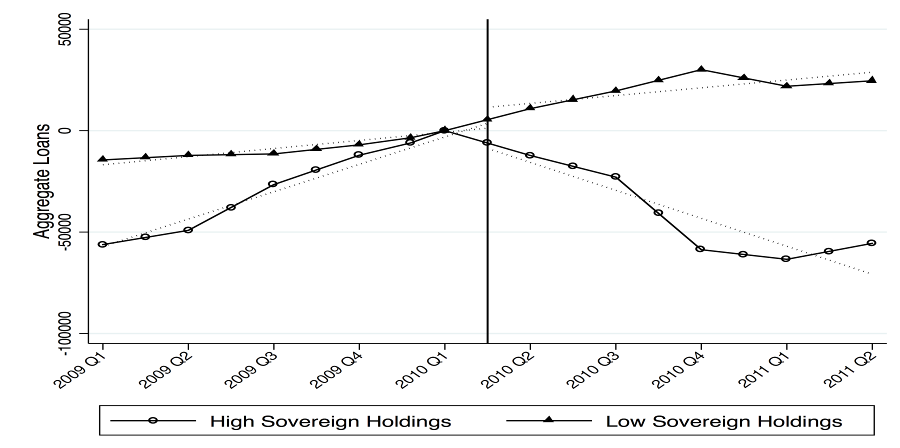
$$\text{Sovereigns}_{b,2010Q1} = \phi_0 + \Gamma \cdot X_{b,2010Q1} + \varepsilon_{b,2010Q1}$$

where $X_{b,2010Q1}$ are bank-specific controls measured at the end of the first quarter of 2010. Importantly, this is the same set of controls used in the paper for the rest of the analysis. Then, we extract the estimated residuals of this regression and we classify a bank as *"High sovereign"* whenever $\hat{\varepsilon}_{b,2010Q1}$ is above the median of the cross-sectional distribution of residuals, and *"Low sovereign"* otherwise. Sorting banks according to their *residual* sovereign holdings helps us to focus only on the cross-sectional variation of their exposure that is not imputable to different bank-specific characteristics. Furthermore, it allows us to replicate more closely a setting that is similar to main regression in the paper. Second, we aggregate by quarter all corporate loans ($\ln(\text{Loans}_{bj,t})$) belonging to our sample that have been granted by banks classified in the two groups. For graphical clarity, in Figure (B.3) we normalize each one of the two time series to zero in 2010:Q1.

Before the shock, the (unconditional) credit supply of banks with higher holdings of sovereigns - if anything - was growing faster than that of banks with lower holdings. Immediately after the shock, we observe a sharp reversal of the lending trend for the group with high sovereign holdings, while banks with lower holdings kept a similar dynamic

Figure B.3. The bank lending channel

This figure illustrates the bank lending channel semi-parametrically by comparing lending to firms from banks with high holdings of Italian sovereign bonds, the most exposed to the sovereign shock, and banks with lower holdings.



for the first three quarters of the post-shock period. This evidence excludes that our results could be driven by a failure of parallel trend, where more exposed banks were cutting credit more than less exposed banks also before the actual shock to sovereign markets.

However, in the main result section of the paper - Figure 3.1 - we provide a more refined version of this analysis. In particular, always consistent with our main analyses, we restrict our attention to the variation in bank credit (on the y-axis in Figure B.3) which is not explained by bank's balance sheet characteristics. To do so, we run a loan-level regression of loans ln(Loans$_{bj,t}$) on a set of bank-level characteristics, and relationship-specific characteristics:

$$\ln(\text{Loans}_{bj,t}) = \psi_0 + \Omega \cdot \bar{X}_{b,t} + \Lambda \cdot \bar{Z}_{bj,t} + \varepsilon_{bj,t}$$

where $\ln(\text{Loans}_{bj,t})$ is the natural logarithm of the value of outstanding loan issued bank b in favor of firm j in quarter t, and $\bar{X}_{b,t}$ and $\bar{Z}_{b,t}$ are four-quarters moving average of our bank-specific and relationship-specific controls. We extract the residuals ($\hat{\varepsilon}_{jb,t}$) of this regression. Sorting banks into "High" and "Low Sovereign" as described above, we aggregate $\hat{\varepsilon}_{jb,t}$ into two time series. As above, we normalize each time series such that they take value zero in 2010:Q1, and plot them over time in Figure 3.1. As discussed in the paper, in this case we find that the two groups present very similar patterns in lending before the decision but more exposed banks start experience a larger decline in lending in the quarters after the Greek bailout. More discussion on the interpretation of these results and on other tests is available in the Section (3.4) of the paper.

B.7 Robustness: Bank lending channel

Here we present a few robustness that we discussed in the first part of the paper (Section 3.4). The objective is to bolster the claim that the sovereign shock had a causal impact on credit.

In Table (B.7), we examine how our results change if we use the full sample of firms, which is both firms with multiple and single relationship in our sample. Column (3) is already presented in the main result (Table 2.2). Here we present the different iterations with the various set of controls and different ways to cluster the standard errors. Overall, we find that sovereign exposure is always negative and significant at the conventional levels. Furthermore, results are also very similar in magnitude to our main results.

Similarly, in Table (B.8), we examine our choice of clustering standard error at bank level by repeating our main specification using firm level cluster. While we argue in the paper that bank clustering is conceptually more correct, here we want to show that this choice is also more conservative. Indeed, we find that standard errors clustered at firm-

Table B.7: The bank lending channel: Alternative sample

This table examines the transmission of the sovereign shock to credit supply via the bank lending channel. The outcome variable is the normalized growth rate in loans (g(Loans)) granted by bank *b* to firm *j* between (2010:Q2-2011:Q1) and (2009:Q2-2010:Q1). The main independent variable is the stock of Italian sovereigns held by the lender at the end of 2010:Q1 scaled by RWA ($\text{Sovereigns}_{2010Q1}$). All regressions include a set of bank-specific controls measured at the end 2010:Q1. Column (1) and (4) include a constant. Column (2) and (3) are within-firm estimates and include firm fixed effects. All regressions are estimated on the full sample that includes both single- and multiple-relationship firms. Column (3) and (4) include relationship-specific controls measured at the end 2010:Q1. Standard Errors are clustered at bank level. *** denotes significance at the 1% level, ** at the 5%, and * at the 10%.

	(1)	(2)	(3)
		g(Loans)	
$\text{Sovereigns}_{2010Q1}$	-0.220***	-0.259***	-0.345***
	(0.020)	(0.022)	(0.023)
ROA_{2010Q1}	4.706***	8.913***	7.324***
	(1.701)	(2.030)	(1.976)
Size_{2010Q1}	0.003***	0.004***	0.006***
	(0.001)	(0.001)	(0.001)
Tier1_{2010Q1}	0.733***	0.748***	0.905***
	(0.049)	(0.059)	(0.057)
Deposits_{2010Q1}	0.160***	0.171***	0.168***
	(0.010)	(0.012)	(0.012)
$\text{Liquidity}_{2010Q1}$	5.733***	5.382***	5.574***
	(0.586)	(0.687)	(0.673)
Net Interbank Debt_{2010Q1}	0.183***	0.197***	0.126***
	(0.019)	(0.021)	(0.021)
Bad Loans_{2010Q1}	-0.623***	-0.706***	-0.339***
	(0.054)	(0.063)	(0.063)
BCC	0.035***	0.043***	0.068***
	(0.006)	(0.006)	(0.006)
Firm Fixed Effect	Y	Y	Y
Relationship Controls	N	N	Y
Cluster SE	Firm	Firm	Firm
Observations	478235	478235	478235
R-squared	0.003	0.372	0.387

level are smaller in magnitude, and this difference is generally large. This result confirms our choice of clustering errors at bank level.

In Table (B.7), we examine whether our results may be driven by heterogeneity in governance across banks. The idea is that certain banks may be characterized by a different governance structure, which may be correlated to how lending was affected by the Greek bailout as well as to sovereign exposure. We consider two main classes of banks that may divert from the standard private bank governance model: Credit Cooperative and Foreign banks. In general, we find results that are re-assuring for us. In particular, we detect no significant difference in the extent to which these banks react to the sovereign shock. This excludes that these banks may have driven our main results.

Credit Supply across small and large firms

In the paper, we have shown that banks reduced credit because of the sovereign shock and this credit supply shock led to an overall reduction in firm credit. Furthermore, we have documented that this inability to smooth the credit shock was more prevalent among small firms. There may be two explanations for this result. First, smaller firms may be less able to respond to a reduction in credit within the banking sector. Second, banks may have cut credit more extensively to smaller firms. As we discuss in the paper, we believe that the first explanation is prevalent in our setting. To show this in the data, we repeat our within-firm analysis estimating the effect of the sovereign shock across small and large firms. In this way, we can isolate the heterogeneous effect of the shock across size keeping credit demand constant. Results are presented in Table (B.10): as anticipated, we find no difference in the shock effect across small and large: the coefficient for the small is indeed negative, but it is very small in size and non-significant.

Firm Fixed effect and Credit Demand

As discussed in the paper, other studies employing a similar within-firm identification strategy have treated the estimated fixed effects as nuisance parameters ([**?**,47,130,132,225]). However, to the extent that they proxy real demand-side shocks, the estimated fixed effects may convey useful information on the transmission of the sovereign shock to the real economy. Based on this argument, we use the estimated firm fixed effect - $\hat{\rho}_j$- as a control in our between-firm estimator.

To validate this approach, we examine to what extent $\hat{\rho}_j$actually captures variation in credit demand across firms. In particular, we expect to observe a significant correlation between the firm's fixed-effect estimates and proxies of riskiness and demand for credit, which have been used by the previous literature in finance. In Table (B.11), we find a strong, positive correlation between the fixed effects and a firm's growth in revenues and assets between 2009 and 2010. Similarly, the $\hat{\rho}_j$ are positively correlated with the credit score of the borrower after the onset of the crisis. While the estimates $\hat{\rho}_j$ are likely noisy, these findings corroborate the hypothesis that the firm fixed-effect estimated by model (3.1) capture and control for relevant information about changes firms' credit demand and creditworthiness.[50]

B.8 Robustness: Real effects of sovereign crisis

Lastly, we present here the result where we study how the exposure to the sovereign shock affects firms across industries that are more or less dependent on external finance (Figure B.12). Dependence on external finance is measured using the RZ index, as developed in the seminar work [159]. It is computed at the two-digit SIC level, as described in the data

50. We also find a significant and sizable correlation with asset and revenues growth measured over a two-year window (2009-2011), rather than one year.

section of the Appendix. As we discussed in the paper, this analysis shows that firms that are more dependent on external finance experience a larger drop in employment growth, measured using payroll data. Variation across different level of RZ explains a large share of the variation in employment. However, the same does not hold for investment and credit, for which the interaction coefficient is non-significant and small in size.

Table B.8: The bank lending channel: Alternative clustering

This table examines the transmission of the sovereign shock to credit supply via the bank lending channel. The outcome variable is the normalized growth rate in loans (g(Loans)) granted by bank *b* to firm *j* between (2010:Q2-2011:Q1) and (2009:Q2-2010:Q1). The main independent variable is the stock of Italian sovereigns held by the lender at the end of 2010:Q1 scaled by RWA ($\text{Sovereigns}_{2010Q1}$). All regressions include a set of bank-specific controls measured at the end 2010:Q1. Column (1) and (4) include a constant. Column (2) and (3) are within-firm estimates and include firm fixed effects. The models in Column (1)-(3) are estimated on the sample of firms with multiple lending relationships. The model in Column (4) includes single- and multiple-relationship firms. Column (3) and (4) include relationship-specific controls measured at the end 2010:Q1. Standard Errors are clustered at firm level or bank level, as reported in the third-last row. *** denotes significance at the 1% level, ** at the 5%, and * at the 10%.

	(1)	(2)	(3)	(4)
	g(Loans)			
$\text{Sovereigns}_{2010Q1}$	-0.202**	-0.202***	-0.309**	-0.309***
	(0.082)	(0.018)	(0.124)	(0.019)
ROA_{2010Q1}	4.901	4.901***	4.923	4.923***
	(8.258)	(1.561)	(9.767)	(1.506)
Size_{2010Q1}	0.004	0.004***	0.007	0.007***
	(0.006)	(0.001)	(0.007)	(0.001)
Tier1_{2010Q1}	0.666***	0.666***	0.785***	0.785***
	(0.235)	(0.045)	(0.276)	(0.043)
Deposits_{2010Q1}	0.147***	0.147***	0.140**	0.140***
	(0.056)	(0.010)	(0.070)	(0.009)
$\text{Liquidity}_{2010Q1}$	5.254	5.254***	4.669	4.669***
	(3.519)	(0.538)	(4.080)	(0.522)
$\text{Net Interbank Debt}_{2010Q1}$	0.172*	0.172***	0.115	0.115***
	(0.093)	(0.018)	(0.172)	(0.017)
$\text{Bad Loans}_{2010Q1}$	-0.603***	-0.603***	-0.205	-0.205***
	(0.199)	(0.050)	(0.349)	(0.049)
BCC	0.036	0.036***	0.072**	0.072***
	(0.026)	(0.005)	(0.032)	(0.005)
Firm Fixed Effect	N	N	N	N
Relationship Controls	N	N	Y	Y
Cluster SE	Bank	Firm	Bank	Firm
Observations	533904	533904	533904	533904
R-squared	0.003	0.003	0.044	0.044

Table B.9: The bank lending channel: Foreign and cooperative banks

This table investigates the channels of transmission of the sovereign shock through banks' balance sheet. We investigate the heterogeneity across banks with different governance and ownership structure. The interaction variables include: Foreign Bank (a dummy equal one if the bank is a subsidiary of a foreign bank), BCC (a dummy equal one if the bank is a Cooperative bank). All interaction variables are also included as a control in the regression. The outcome variable is the normalized growth rates in term loans (g(Loans)). The independent variables of interest are the exposure of the lender to Italian sovereigns ($\text{Sovereigns}_{2010Q1}$), and its interactions with different proxies of the transmission channels. All regressions include a set of bank-specific and relationship-specific controls are measured at the end 2010:Q1. Every specification contains firm fixed effects and it is estimated on the sample of firms with multiple credit relationships. Standard Errors are clustered at bank level. *** denotes significance at the 1% level, ** at the 5%, and * at the 10%.

	(1)	(2)
	g(Loans)	
$\text{Sovereigns}_{2010Q1}$	-0.351**	-0.409**
	(0.139)	(0.173)
$\text{Sovereigns}_{2010Q1} \cdot \text{Foreign}$	0.222	
	(0.401)	
$\text{Sovereigns}_{2010Q1} \cdot \text{BCC}$		0.154
		(0.156)
Foreign	-0.023	
	(0.058)	
BCC	0.0676 *	0.049
	(0.037)	(0.042)
Bank Controls	Y	Y
Relationship Controls	Y	Y
Firm Fixed Effect	Y	Y
Cluster SE	Firm	Firm
Observations	478235	478235
R-squared	0.387	0.387

Table B.10: The bank lending channel: Heterogeneity by firm size

This table examines the heterogeneity of bank lending channel across firms of different size. The outcome variable is the normalized growth rate in loans (g(Loans)) granted by bank b to firm j between (2010:Q2-2011:Q1) and (2009:Q2-2010:Q1). The main independent variable is the stock of Italian sovereigns held by the lender at the end of 2010:Q1 scaled by RWA ($\text{Sovereigns}_{2010Q1}$). The interaction variables is a dummy equal to one if firm j's revenues in 2009 are below 2 Million Euros in 2009 (Small Firm_{2009}). All regressions include a set of bank-specific controls measured at the end 2010:Q1. Column (1) and (4) include a constant. Column (2) and (3) are within-firm estimates and include firm fixed effects. The models in Column (1)-(3) are estimated on the sample of firms with multiple lending relationships. The model in Column (4) includes single- and multiple-relationship firms. Column (3) and (4) include relationship-specific controls measured at the end 2010:Q1. Standard Errors are clustered at firm level. *** denotes significance at the 1% level, ** at the 5%, and * at the 10%.

	(1)	(2)	(3)	(4)
	g(Loans)			
$\text{Sovereigns}_{2010Q1}$	-0.556***	-0.322**	-0.525***	-0.305**
	(0.179)	(0.141)	(0.143)	(0.140)
$\text{Sovereigns}_{2010Q1} \cdot \ln(\text{Revenues}_{2009})$	0.028		0.026	
	(0.023)		(0.018)	
$\text{Sovereigns}_{2010Q1} \cdot \text{Small Firm}_{2009}$		-0.044		-0.038
		(0.056)		(0.050)
ROA_{2010Q1}	7.148	7.253	5.270	5.162
	(11.514)	(11.520)	(9.977)	(9.963)
Size_{2010Q1}	0.006	0.006	0.008	0.008
	(0.008)	(0.008)	(0.007)	(0.007)
Tier1_{2010Q1}	0.911***	0.907***	0.839***	0.822***
	(0.282)	(0.282)	(0.274)	(0.277)
Deposits_{2010Q1}	0.167**	0.168**	0.145**	0.143**
	(0.074)	(0.074)	(0.073)	(0.073)
$\text{Liquidity}_{2010Q1}$	5.637	5.607	4.948	4.882
	(5.310)	(5.312)	(4.275)	(4.234)
$\text{Net Interbank Debt}_{2010Q1}$	0.126	0.126	0.070	0.081
	(0.175)	(0.174)	(0.173)	(0.174)
$\text{Bad Loans}_{2010Q1}$	-0.339	-0.338	-0.167	-0.180
	(0.352)	(0.350)	(0.369)	(0.366)
BCC	0.069*	0.069*	0.083***	0.081**
	(0.036)	(0.036)	(0.032)	(0.032)
Firm Fixed Effect	Y	Y	N	N
Bank Controls	Y	Y	Y	Y
Relationship Controls	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y
Observations	478235	478235	533904	533904
R-squared	0.387	0.387	0.050	0.049

Table B.11: Real effects of the sovereign crisis: Fixed Effects and demand-side shocks

This table investigates the correlation between the fixed effects estimated by model (3.1) on the sample of firms with multiple lending relationships appearing in the CADS database with proxies of firms demand, investment opportunities, and creditworthiness. The right-hand side variables in include revenues' growth between the fiscal years 2009 and 2011 (gr(Revenues)), growth in fixed assets (gr(Inv)), credit rating at the end of fiscal year 2011 (Credit Rating$_{2011}$), and the logarithm of revenues in 2009 (ln(Revenues$_{2009}$)). *** denotes significance at the 1% level, ** at the 5%, and * at the 10%.

	(1)	(2)	(3)	(4)	(5)
			$\hat{\rho}$		
gr(Revenues)	0.092***			0.081***	0.082***
	(0.002)			(0.002)	(0.002)
gr(Inv)		0.089***		0.076***	0.075***
		(0.002)		(0.002)	(0.002)
Credit Rating 2011			0.004***	0.007***	0.008***
			(0.000)	(0.000)	(0.000)
ln(Revenues$_{2009}$)					0.005***
					(0.001)
Observations	141374	141374	141374	141374	141374
R-squared	0.017	0.018	0.001	0.032	0.032

Table B.12: Real effects of the sovereign crisis: Dependence on external finance

This table examines the effects of the sovereign crisis on corporate investments and employment transmitted via the lending channel across firms with heterogeneous dependence on external finance. The dependent variables are two proxies of firm investments and employment. The main independent variable is the weighted average of the exposure to Italian sovereigns of firm j's lenders (Sovereigns$^{AVE}_{2010Q1}$). We interact with the firm level shock with a proxy of firm's dependence on external finance (RZ Index). All regressions include a set of weighted averaged bank-specific and relationship-specific controls are measured at the end 2010:Q1. All regressions include province fixed effects and industry fixed effects measured at the end of 2010:Q1. Column 2, 4 and 6 control for unobserved demand-side shocks using the firm fixed effect $\hat{\rho}_j$ estimated in the baseline regression of the bank lending channel (equation (3.1)). Standard Errors are clustered at lead bank level. *** denotes significance at the 1% level, ** at the 5%, and * at the 10%.

	(1)	(2)	(3)	(4)	(5)	(6)
	g(Tot Loans)		gr(Empl)		gr(Inv)	
Sovereigns$^{AVE}_{2010Q1}$	-0.209***	-0.160***	-0.078*	-0.068	-0.028	-0.016
	(0.057)	(0.027)	(0.042)	(0.042)	(0.041)	(0.041)
Sovereigns$^{AVE}_{2010Q1}$ · RZ	-0.010	-0.004	-0.016**	-0.014**	0.007	0.009
	(0.006)	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)
$\hat{\rho}$		0.834***		0.154***		0.209***
		(0.004)		(0.006)		(0.005)
Industry and Province Fixed Effects	Y	Y	Y	Y	Y	Y
Bank Controls	Y	Y	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y	Y	Y
Observations	139013	139013	139013	139013	139013	139013
R-squared	0.111	0.689	0.027	0.042	0.012	0.028

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