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Markups and Productivity under Heterogeneous Financial Frictions*

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Abstract

We incorporate heterogeneous financial frictions in a setting of monopolistically competitive firms with endogenous markups. Before producing, firms must pledge collateral to obtain a bank loan, needed to cover part of production costs. Firms differ both in productivity and in their cost of raising collateral. Firm-specific financial frictions, together with productivity, therefore figure in the equilibrium expressions of prices and markups. We validate our theoretical results on a representative sample of European manufacturing firms surveyed during the financial crisis. Guided by our model we retrieve from balance-sheet data firm-specific measures of access to finance, total factor productivity and markups, and then use these variables to estimate our equilibrium equations structurally. Consistent with our model, we show how heterogeneity in access to finance explains part of the dispersion of prices and markups, even after controlling for firms' productivity and size. In the aggregate industry equilibrium, the amount of collateral required by banks significantly affects the cost pass-through to prices.

Keywords: Financial frictions, heterogeneous firms, markups

JEL Codes: D24; E22; F36; G20

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1 Introduction

A growing literature examines how financial frictions, interacting with firms' characteristics, affect economic outcomes. In particular, in addition to productivity, credit constraints have been found to be an important determinant of exports or innovation.[1] Financial frictions in the form of size-dependent borrowing constraints (Gopinath et al., 2017) or heterogeneous dependence on external finance (Larrain and Stumpner, 2017) have also been shown to influence the allocation of capital across firms, hence aggregate productivity. Most of the models developed in this literature, however, assume CES preferences, and thus abstract from the interplay of financial frictions with firm-level markups. Still, there is growing empirical evidence that firm-level markups tend to be dispersed rather than concentrated at some single value.[2] In addition, the evidence shows that firms are strongly heterogeneous in their access to external finance, not only in productivity and markups.[3]

Motivated by these findings, this paper incorporates firm-specific financial frictions in a setting of monopolistically competitive firms with heterogeneous productivity and endogenous markups (as in Melitz and Ottaviano, 2008). Before producing, firms must obtain a bank loan to cover part of production costs. To get the loan, firms must post the amount of collateral (tangible assets) that the bank requires. Firms are heterogeneous not only in productivity, but also in their cost of accessing finance: the cost of raising collateral is lower for some firms, a feature that we define as financial capability. Having obtained the loan, firms enter the market and set profit maximizing prices and markups.

The main implication here is that financial capability (the relative cost advantage of each firm in raising collateral) and collateral requirements (the quantity of collateral demanded by banks) figure, together with productivity, in the equilibrium expressions of firm's prices and markups. These financial frictions affect the industry equilibrium

[1]See among others Minetti and Zhu (2011); Gorodnichenko and Schnitzer (2013); Manova (2013); Peters and Schnitzer (2015); Muuls (2015); Chaney (2016); Bonfiglioli et al. (2018).

[2]See for example Atkin et al. (2015); De Loecker et al. (2016); Mrázová et al. (2017).

[3]Irlacher and Unger (2016) use World Bank firm-level data across countries to decompose the total variation of access to credit (proxied as tangible assets over total assets) into within- and between-industry variation, finding that roughly 80% of the variation is within (narrowly defined) industries, even after controlling for firm-level characteristics.

through different channels. Our model shows that, for any given level of collateral requirement and productivity, the more financially capable firms do not translate their entire financing cost advantage into lower prices, but rather retain relatively higher margins in equilibrium. This implies that heterogeneity in access to finance can explain part of the dispersion in firms' prices and markups, even after controlling for firms' productivity and size. We also find that for any given level of financial capability across firms, and hence ex-ante dispersion of markups, the amount of collateral that banks require affects the pass-through of costs to prices in the aggregate industry equilibrium. This implies that the extent of the pro-competitive adjustment of industries following, say, episodes of trade liberalization is (also) a positive function of the amount of credit available to firms: if access to credit is relatively tight, the pass-through will be *ceteris paribus* lower.

We test our model empirically on a large representative sample of manufacturing firms in seven European countries surveyed during the financial crisis (the Efige dataset).[4] The cross-country nature of the data allows us to draw conclusions that do not depend on specific national institutional features. For each firm in the Efige survey we have linked balance-sheet data from 2002 to 2013, retrieved via Bureau van Dijk's Amadeus database. The survey also includes a number of additional firm-specific characteristics not typically found in balance sheet (e.g. innovation activities, firm-bank relationships), which we use to check the robustness of our results.

Using our model, we first retrieve from balance-sheet data a non-parametric measure of each firm's financial capability, our firm-level proxy of access to finance. We then compute total factor productivity (TFP) purged of the effects of heterogeneity in access to finance, and retrieve firm-specific markups following the methodology proposed by De Loecker and Warzynski (2012).[5] We then use the estimated financial capability, TFP

[4]The European Firms in the Global Economy (Efige) dataset is a harmonized cross-country dataset containing quantitative as well as qualitative information on around 150 variables for a representative sample of some 15,000 manufacturing firms surveyed in 2010 in Austria, France, Germany, Hungary, Italy, Spain, and the United Kingdom.

[5]In our model more financially capable firms get fixed assets at cheaper costs. To obtain unbiased productivity and markup estimates we have modified the standard algorithms of TFP estimation (Wooldridge, 2009 or Ackerberg et al., 2015) to incorporate a control for the effects of financial capability. We then apply the method of markup estimation proposed by De Loecker and Warzynski (2012), which relies on a control function for unobserved productivity and allows for flexible production technologies and a different range of production inputs. In a robustness check we also address the issue of a potential bias

and markups to estimate the equilibrium equations structurally. All the firm-specific parameters can be estimated using simple balance-sheet data. The results confirm the insights of the model, and are robust to a battery of sensitivity checks and the use of other (reduced-form) proxies of access to finance currently used in the literature.

Our framework draws a number of features from the financial literature. From Vig (2013) and Brumm et al. (2015) we adopt the general idea that the quantity and quality of firms' tangible assets is related to the amount of loan collateral that banks require. To develop a micro-founded channel for firms' heterogeneity in financial capability, we exploit the fact that tangible assets differ in of 'redeployability' (Berger et al., 2011; Campello and Giambona, 2013; Cerqueiro et al., 2016). The idea is that redeployable tangible assets (e.g. land) are less firm-specific, can be more easily sold, and hence readily accepted as collateral.[6] We posit that some firms are more able to obtain these redeployable assets and so benefit from overall lower financing costs. We also exploit evidence that larger firm size is associated with larger loans (Rampini and Viswanathan, 2013). Hence in our setting the amount of loans requested is proportional to total production costs.

The paper also speaks to a literature that has introduced financial frictions in models of firm heterogeneity and international trade. Chaney (2016) studies liquidity-constrained exporters that, due to imperfect financial markets, must rely on their own existing liquidity to cover entry costs into foreign markets. Firms differ in the extent of liquidity constraints, as they inherit an exogenous amount of assets that vary depending on the firm's history of accumulating cash. As in Chaney (2016), firms in our framework face a liquidity constraint at entry into production (into exports in Chaney, 2016). As in Manova (2013), firms in our framework can post tangible assets to obtain bank loans to cover part of their production costs (exports costs in Manova, 2013). In our model firms also differ in the assets that they can pledge as collateral and hence, similar to Chaney (2016), they have heterogeneous access to finance.

in the first-order condition of De Loecker and Warzynski (2012) when the financial constraint is binding, exploiting information on the outcome of firms' credit applications available in the survey.

[6]Benmelech et al. (2005) find that firms with more redeployable pledgeable assets get larger loans at lower interest rates. Benmelech and Bergman (2009) show that more redeployable collateral results in higher loan-to-value ratios.

Importantly, both Manova (2013) and Chaney (2016) incorporate credit constraints in a CES framework of heterogeneous firms, leading to a complete pass-through, as markups are constant in their models.[7] In our model with variable markups, by contrast, the pass-through is incomplete. This relates to the work of De Locker et al. (2016), who document that trade liberalization may generate incomplete cost pass-through to prices. They derive this result without committing to any particular market structure for measuring markups, and thus remain agnostic on which fundamentals generate the incomplete pass-through. In this paper we show both theoretically and empirically that in a setting with linear consumer demand and monopolistic competition (as in Melitz and Ottaviano, 2008), heterogeneous financial frictions contribute to an incomplete pass-through.

We are not the first to posit credit constraints in models of heterogeneous firms with endogenous markups. Egger and Seidel (2012), in particular, also introduce liquidity constraints and the use of a common collateral requirement proportional to firms' production costs in order to obtain loans. Differently from our case, however, there is no role for heterogeneity in access to finance. As a result, their profit-maximizing quantities and prices are affected by financial frictions only through a shift in the cost cutoff parameter of the model. Peters and Schnitzer (2015) place financial frictions within a variable markup framework with endogenous technology adoption, in which the purchase of the advanced technology has to be financed externally. However, as they assume that technology adoption results in the increase in the markup by a fixed amount, they do not work out the implications of financial frictions for the pass-through effect.

Finally, our paper relates indirectly to the recent literature on the implications of financial frictions for capital allocation and productivity, as the issue of resource misallocation is beyond our present scope. Within this literature, Larrain and Stumpner (2017) develop a multi-sector model in which two groups of firms face heterogeneous access to finance in the form of different costs of capital: only one group can tap the capital market, while the

[7] Bonfiglioli et al. (2018) also study how financial frictions affect firm-level heterogeneity and trade, always in a CES setting. They build a model with endogenous productivity differences across firms depending on investment decisions at the entry stage. They show that financial frictions lower the value of investing in bigger projects with more dispersed outcomes, thus reducing firm size and hindering the volume of exports.

other has to borrow from a monopolist bank. Crucially, the two groups of firms also have different group-specific markups. Larrain and Stumpner (2017) provide reduced-form evidence that episodes of financial liberalization work their effects on aggregate productivity also through markups, which is consistent with one of our findings. However, unlike these authors, we do not need financial shocks to derive our results, as in our framework the mere existence of firm-specific financial frictions affects the pass-through. Gopinath et al. (2017) introduce the idea of size-dependent borrowing constraints in a small open economy with heterogeneous firms and capital adjustment costs. They show how a model including financial frictions that depend on firm size better replicates actual firm behavior (as seen in the data), with capital inflows going to the firms that have greater net worth but are not necessarily more productive, generating potential misallocation. Consistent with their results, our data indicate that firms with higher turnover face systematically lower collateral requirements.

The rest of the paper is organized as follows. We present our theoretical framework in Section 2. Section 3 describes the data and our estimation routines for financial capability, productivity and markups, and reports sensitivity and robustness checks of these measures. In Section 4 we use these variables to test our main prediction at the firm level. In Section 5 we work out the implications of financial frictions for the pass-through effect. Section 6 concludes.

2 The theoretical framework

Our setting posits two exogenous sources of heterogeneity affecting individual firms' strategies: productivity, i.e. the marginal costs relating to production; and financial capability, i.e. the firms' relative cost advantage in raising collateral. These variables are uncorrelated ex-ante, as they are drawn from independent probability distributions.[8] Moreover, they are considered sequentially by firms: first, given its productivity, a firm evaluates its (ex-ante unconstrained) level of production; second, as it must finance part of its production costs, the firm learns about the amount of collateral requested by the bank and

[8] We provide evidence in the empirical section of the paper consistent with this assumption.

obtains assets to pledge as collateral, at a cost based on its financial capability. Having obtained the loan, and knowing its actual cost of access to finance, the firm sets optimal (profit-maximizing) prices, quantities and markups.

We now model these different sources of heterogeneity, and then, after characterizing a demand function allowing for variable markups, derive the firm-level equilibrium.

2.1 Productivity

We consider an economy with L consumers, each supplying one unit of labor. Consumers allocate their income between two goods: one homogeneous, supplied by perfectly competitive firms, and one differentiated, produced under monopolistic competition.

Conditional on adequate access to financial resources, firms, as in Melitz and Ottaviano (2008), produce using only the labor input, inelastically supplied in a competitive market. The production of the homogeneous good requires one unit of labor, which implies a wage normalized to one for both sectors. Both the homogeneous and the differentiated good are produced under constant returns to scale, but entry into the differentiated-goods industry involves a sunk cost f_E. Firms are heterogeneous in productivity, with firm-specific marginal cost of production $c \in [0, c_M]$ drawn randomly from a given probability distribution. In the absence of financial frictions, the equilibrium output level $q(c)$ of a firm with cost c will thus be equal to the total demand for its own product variety.

2.2 Financial capability

Liquidity-constrained firms need to borrow from banks in order to finance a fixed share $\rho \in [0, 1]$ of their production costs $cq(c)$.Firms have a positive initial endowment out of which they can purchase tangible assets to use as collateral, and pay the sunk entry cost f_E.[9] Given production technology, firms characterized by greater output $q(c)$ also have higher production costs $cq(c)$, whose financing requires a larger volume of loans $\rho cq(c)$. This type of setup is supported by empirical evidence. In our data, regressing a firm's

[9]Expenditure on collateral and the sunk cost f_E are factored into the entry decision via the expected profit equation, and thus figure in the expression for the industry equilibrium.

(log) turnover on its bank liabilities yields a positive and significant coefficient.[10]

Another key feature of our framework, also in line with empirical evidence, is that firms differ in access to external finance.[11] To encompass this in the model, we exploit the standard distinction of tangible assets between redeployable (land, plants and buildings) and non-redeployable ones, such as machinery and equipment (see e.g. Campello and Giambona, 2012). Redeployable assets are easier to liquidate in organized markets: they are therefore readily be usable as collateral and so facilitate borrowing. Non-redeployable assets are more firm-specific, and their value deteriorates over time (owing, say, to technological obsolescence): as such, they are less easily used as collateral.[12]

We posit that firms use tangible assets as collateral (as in Manova, 2013), and that they differ in their ability to negotiate the price of their redeployable assets, each firm having a specific level of negotiating skill $\tau \in [0, 1]$ randomly drawn from a probability distribution and independent of marginal costs $c \in [0, c_M]$. Firms with greater ability τ end up paying relatively less for their redeployable assets. The function $C(\tau)$ then maps the marginal cost of collateral for the firm whose ability level is τ, with $C(\tau)$ strictly decreasing in τ.[13] Hence we can define the ability cutoff $\widetilde{\tau} < \tau$ such that $C(\widetilde{\tau}) = C_{max}$; that is, a firm with ability $\widetilde{\tau}$ would obtain no advantage in the price of redeployable assets with respect to other firms, i.e. its marginal cost of collateral would be the upper bound of the cost function $C(\tau)$. It follows that the function

$$\theta(\tau) = C(\widetilde{\tau}) - C(\tau) \tag{1}$$

is increasing in τ and measures the cost advantage in terms of raising collateral that a firm with ability τ will have vis-à-vis the cutoff firm. We call that advantage $\theta(\tau)$ a firm's

[10] We use the item "Loans" reported in balance-sheet data to test for this stylized fact, which incorporates firms' liabilities to credit institutions. The relation is robust to the inclusion of firm fixed effects. More details are available on request.

[11] Like Irlacher and Unger (2016), we find a high dispersion of access to credit (proxied as tangible assets over total assets) across firms within narrowly defined industries (4-digit NACE), even after controlling for firm-level characteristics (e.g. productivity).

[12] More in general, under asset-based lending, collateralizable assets include inventory, accounts receivable, machinery and equipment, real estate or the cash flow.

[13] See Appendix A for a micro-founded characterization of this function. In general our results hold with any specification of a functional form for the cost of collateral, as long as $\partial C(\tau)/\partial\tau < 0$.

"financial capability". By definition, the cutoff firm $\widetilde{\tau}$ has no cost advantage; in other words, its financial capability equals $\theta(\widetilde{\tau}) = 0$.

The implications of heterogeneity in financial capability can be illustrated by considering the case in which all firms have the same ability $\bar{\tau}$. In this case, firms in the industry would all end up with the same marginal cost of collateral $C(\bar{\tau})$. As a result, productivity would be the only firm-specific variable characterizing the industry equilibrium, while financial frictions would work only through changes in collateral requirements, typically modeled as entry barriers to the industry. Introducing heterogeneity in financial capability $\theta(\tau)$ too, as a second cost component in addition to production costs, generates a richer interaction between productivity and financial frictions in the industry equilibrium.

2.3 Financing of firms

In order to grant a loan, banks require $\beta > 0$ units of collateral for each unit of output. That banks require an amount of collateral that is proportional to output is an empirical regularity that has been reported in the literature (Rampini and Viswanathan, 2013) and is confirmed in our data: regressing firms' bank liabilities on tangible assets (as a proxy for collateral) yields a positive and significant coefficient, supporting the proportional relationship between output and collateral posted. The collateral requirement β is set ex-ante by the bank and can vary from industry to industry (as e.g. in Manova, 2013). Hence, a firm with marginal costs c and total output $q(c)$ has to pledge an amount of collateral $\beta q(c)$ in order to be granted the loan.[14]

Firms that fund a share $\rho > 0$ of their total production costs $cq(c)$ have to repay $R(c)$ to banks. Repayment is made with exogenous probability $\lambda \in (0, 1)$; with probability $(1 - \lambda)$ the financial contract is not enforced, the firm defaults, and the bank seizes the collateral $\beta q(c)$. The bank's participation constraint is:

$$-\rho c q(c) + \lambda R(c) + (1 - \lambda)\beta q(c) \geq 0 \tag{2}$$

[14] We do not need an upper bound to β, because collateral will figure into the firm's profit function as a cost, so if the unit requirement β is too high with respect to the firm's optimal size, it will simply decide not to produce (free exit). More in general, our results hold with different specifications of a functional form for collateral requirement, as long as it is exogenous to firms.

That is, banks will make the loan when its value $\rho c q(c)$ is at least equal to the expected return, either in the form of regular repayment $R(c)$ or through seizure of the collateral $\beta q(c)$ in case of default. Given perfect competition in the banking sector, the participation constraint holds with equality for all banks. In turn, firms will apply for a loan if their liquidity constraint is satisfied, i.e. if net revenues are at least equal to the repayment $R(c)$. Specifically,

$$p(c,\tau)q(c,\tau) - (1-\rho)cq(c,\tau) + \theta(\tau)q(c,\tau) \geq R(c,\tau) \tag{3}$$

That is, a firm applies for a loan if the difference between revenues and the internally financed portion of the costs, net of the firm's cost advantage $\theta(\tau)$ in generating the required amount of collateral, is at least equal to the repayment obligation.[15]

More in general, in our framework the channel that can explain heterogeneity in access to finance is linked to asset redeployability. Alternatively, one could consider the relationship lending literature, which studies how relations between managers and banks increase the availability of funds and lower lending rates.[16] Viewing this literature in our own setting, one could rate firms as more or less financially capable depending on their share τ of managers more skilled in bargaining (or better connected) with banks. The higher the share of these managers, the lower the repayment value of the loan, holding banks' collateral requirement constant. The financial capability cutoff firm would have no managers with such relations ($\widetilde{\tau} = 0$), hence no cost advantage, i.e. $\theta(\widetilde{\tau}) = 0$.[17]

[15] The liquidity constraint incorporates the financial capability $\theta(\tau)$, i.e. it is conditional on the cutoff $\widetilde{\tau}$. The latter has to be endogenized to close the model (see below).

[16] The channels through which bank-manager relations can affect borrowing are fund availability and quantity, or prices and collateral (see Berger and Udell, 1995 and 1998; Cole et al., 2004; Petersen and Rajan, 1995).

[17] As we do not have detailed information on each firm-bank relationship, in the empirical part of the paper we will use the channel of asset redeployability (namely, balance sheet information on tangible assets) in order to retrieve a measure of financial capability from our data.

2.4 Demand

Consumers exhibit love for variety with horizontal product differentiation and quasi-linear preferences as in Melitz and Ottaviano (2008), i.e.

$$U = q_0 + \alpha \int_{i\in\ \Omega} q_i^c \ di - \frac{1}{2}\gamma \int_{i\in\ \Omega} (q_i^c)^2 \ di - \frac{1}{2}\eta \left[\int_{i\in\ \Omega} q_i^c \ di \right]^2 \tag{4}$$

where the set Ω contains a continuum of differentiated varieties, each indexed by i. The term q_0 represents the demand for the homogeneous good, taken as numeraire, while q_i^c corresponds to the individual consumption of variety i of the differentiated good. The parameters α and η index the substitution pattern between the homogeneous and the differentiated good; γ represents the degree of differentiation of varieties $i \in \Omega$.

Conditional on positive demand for the homogeneous good, i.e. $q_0 > 0$, and solving the consumer's utility maximization problem, we can derive the inverse demand for each variety:

$$p_i = \alpha - \gamma q_i^c - \eta \int_{i\in\ \Omega} q_i^c \ di \ , \forall i \in \Omega \tag{5}$$

Inverting (5) we obtain the individual demand for variety i in the set of varieties consumed Ω^*, a subset of Ω for which $q_i^c > 0$, and obtain the following linear market demand system:

$$q_i = L q_i^c = \frac{\alpha L}{\gamma + \eta N} - \frac{L}{\gamma} p_i + \frac{\eta N \overline{p} L}{\gamma(\gamma + \eta N)} \ , \forall i \in \Omega^* \tag{6}$$

In this expression N represents the number of varieties consumed, which is equal to the number of firms in the market, since each firm is a monopolist in the production of its own variety; $\overline{p} = \frac{1}{N} \int_{i\in\ \Omega^*} p_i di$ is the average price charged by firms in the differentiated sector. To get an expression for the maximum price a consumer is willing to pay, we set $q_i = 0$ in the demand for variety i and obtain the following:

$$p_{max} = \frac{\alpha\gamma + \eta N \overline{p}}{\gamma + \eta N} \tag{7}$$

Therefore, as already shown by Melitz and Ottaviano (2008), the prices of varieties of the differentiated good must be such that $p_i \leq p_{max}$ for every variety $i \in \Omega^*$, which in turn implies that Ω^* is the largest subset of Ω that satisfies the price condition above.

2.5 The firm's problem

Each firm in the differentiated sector maximizes the following profit function

$$\Pi(c,\tau) = p(c,\tau)q(c,\tau) - (1-\rho)cq(c,\tau) - \lambda R(c,\tau) - (1-\lambda)\beta q(c,\tau) + \theta(\tau)q(c,\tau)$$

To solve the firm's problem we must consider the cutoff (zero-profit) level of marginal production costs (the free exit condition as in Melitz and Ottaviano, 2008) under, in turn: the bank's participation constraint (2), the demand for the variety produced (6), and the liquidity constraint (3), conditional on financial capability (1). From equation (2) we derive an expression for the repayment function:

$$R(c) = \frac{1}{\lambda}[\rho c - (1-\lambda)\beta]q(c)$$

Plugging this into the profit function and maximizing profits under the linear demand (6) yields the first order condition:

$$p(c,\tau) - \frac{\gamma}{L}q(c,\tau) - c + \theta(\tau) = 0$$

Rearranging the terms above, we obtain the supply curve for the generic (c,τ)-firm:

$$q(c,\tau) = \frac{L}{\gamma}\left[p(c,\tau) - c + \theta(\tau)\right] \tag{8}$$

We can now use the liquidity constraint (3) to derive an expression for the production cost cutoff c_D. Firms whose marginal costs are such that net revenues are not enough to repay the loan will exit the market; hence, the liquidity constraint must hold with equality for the cutoff firm, characterized by marginal production costs c_D. Moreover, this cutoff firm faces an upper bound in prices $p_i = p_{max}$ (see equation 7). We can therefore rewrite the liquidity constraint as follows:

$$p_{max}q(c_D,\tau) - (1-\rho)c_Dq(c_D,\tau) + \theta(\tau)q(c_D,\tau) = R(c_D,\tau)$$

Substituting and rearranging the terms yields a simple expression for p_{max} as a function of the cost cutoff c_D and the cost advantage $\theta(\tau)$:

$$p_{max}(c_D,\tau) = \omega c_D - \phi - \theta(\tau)$$

where $\omega = \frac{\rho}{\lambda} + 1 - \rho$ and $\phi = \frac{1-\lambda}{\lambda}\beta$ are constant terms incorporating the presence of financial constraints in the model.

Our results still depend on the cutoff $\widetilde{\tau}$ with respect to which financial capability $\theta(\tau)$ is calculated. In order to endogenize $\widetilde{\tau}$ in the expression for p_{max}, recall from expression (1) that $\theta(\tau)$ is increasing in τ. Hence, the maximum price charged by a firm in our setting is that of the least financially able firm $\widetilde{\tau}$ having marginal production costs c_D (the 'double' cutoff firm). As $\theta(\widetilde{\tau})$ is the lower bound of $\theta(\tau)$ and is equal to 0 (no cost advantage), it follows that the expression for p_{max} incorporating both the production and the financial capability cutoffs is simply

$$p_{max} = \omega c_D - \phi \tag{9}$$

We can now solve for optimal prices and markups.

2.6 Equilibrium

In equilibrium, the demand for each variety equals supply:

$$\left[\frac{\alpha\gamma}{\gamma+\eta N} + \frac{\eta N\overline{p}}{\gamma+\eta N} - p(c,\tau)\right]\frac{L}{\gamma} = \frac{L}{\gamma}[p(c,\tau) - c + \theta(\tau)]$$

Recalling the expressions for p_{max} in (7) and (9), substituting it into the above equation and rearranging, we obtain the equilibrium price charged by a (c,τ)-firm heterogeneous in marginal costs and financial capability, for a given level of collateral requirement β:

$$p(c, \tau) = \frac{1}{2} \left[\omega c_D + c - \phi - \theta(\tau) \right] \tag{10}$$

Subtracting the marginal cost c, we derive the expression of the equilibrium markup:

$$\mu(c, \tau) = p(c, \tau) - c = \frac{1}{2} \left[\omega c_D - c - \phi + \theta(\tau) \right] \tag{11}$$

As in Melitz and Ottaviano (2008), the equilibrium markup charged by a (c, τ) firm is increasing in the production cost cutoff c_D and decreasing in the firm-specific marginal cost of production c. In our framework, however, the imperfect nature of financial markets (as captured by the parameters ω and ϕ), and the heterogeneity of firms in financial capability $\theta(\tau)$ both affect the expression for the markup. In particular, as in the case of productivity differences, the more financially capable firms do not transfer their entire cost advantage $\theta(\tau)$ in raising the collateral into lower prices, but instead retain relatively higher margins. The markup is also affected by the collateral requirement β, as the latter enters in the expression of parameter ϕ and in the expression of the cutoff c_D.[18] To verify the extent to which financial frictions affect the equilibrium level of markups, we test equation (11) structurally in the data.

3 Data and estimation of covariates

3.1 Firm-level data

Our firm-level data come from the survey on European Firms in a Global Economy (Efige), a research project funded by the European Community's Seventh Framework Programme (FP7/2007-2013). The dataset comprises some 150 variables for a representative sample of nearly 15,000 manufacturing firms in Austria, France, Germany, Hungary, Italy, Spain, and the United Kingdom (Table 1). The sample is stratified by industry, region and firm size. Firms smaller than 10 employees are excluded from the survey, which instead

[18] Appendix B proves the existence and uniqueness of c_D and shows how the collateral requirement figures in its expression.

oversamples firms with more than 250 employees in order to allow for adequate statistical inference for this size class. The firm-level data in Efige has been matched with balance-sheet data drawn from Bureau van Dijck's Amadeus database, collected from 2002 to 2013. Descriptive statistics are reported in Appendix D.[19]

Table 1: Efige sample size, by country

Country	Number of firms
Austria	443
France	2,973
Germany	2,935
Hungary	488
Italy	3,021
Spain	2,832
UK	2,067
Total	14,759

The use of a dataset spanning a number of countries allows us to employ country fixed effects so as to wipe out institutional features that might affect the relationship between markups, productivity and financial capability. Moreover, the panel feature, which we exploit through the balance-sheet data, allows us, in a number of specifications, to include a full set of firm fixed effects in order to neutralize possible unobserved heterogeneity at firm level that may drive the results. In what follows, therefore, we trace our main covariates at firm-year level.

3.2 Estimation of financial capability $\theta(\tau)$

We start with the observation that certain firms might be able to obtain collateral at lower cost, a capability gauged by parameter τ. Firms with greater τ would thus get a cost advantage over the least able (cutoff) firm, i.e. $\theta(\tau) > 0$. In our framework collateral consists of tangible assets (TA). All the firms in an industry are required to collect the same amount β of TA per unit of output to use as collateral. It follows that firms of similar size in the same industry, and with similar ability to raise collateral, should have *ceteris*

[19]The complete questionnaire is available at www.efige.org. For detailed information on the distribution of firms by country/size class and industry, as well as a validation of the data vs. official statistics, and the weighting scheme see Altomonte and Aquilante (2012).

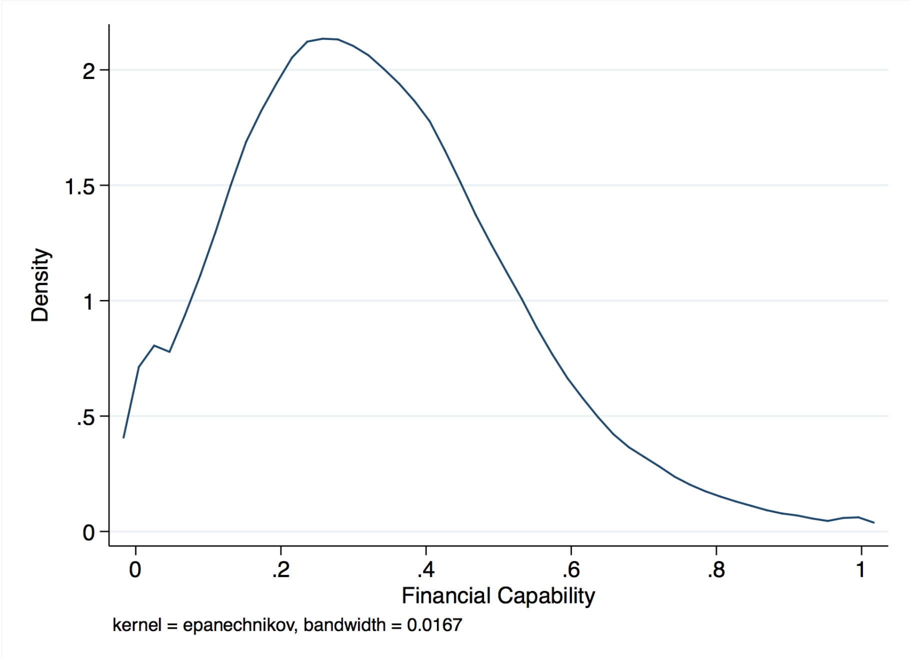
paribus similar book values of tangible assets (i.e. collateral) in their balance sheets.[20] Firms with similar size but more ability, and thus greater financial capability $\theta(\tau)$, should instead have less book value of TA with respect to the cutoff firm. Hence, to estimate a proxy for financial capability we proceed in three stages. First, we create bins of firms of the same size within each industry (deciles of turnover, with quintiles and twentiles used to check robustness). Second, for each bin within each industry (at the 2 or 3-digit NACE level of aggregation), we identify the upper bound of firms' nominal tangible assets, calculated as the average book value of the top 5% firms in terms of TA (robustness check with 1%). This value should represent the value of TA in the cutoff firm, i.e. the firm that acquires collateral at the highest cost within the given size/industry bin. Finally, we compute firm-year financial capability $\theta(\tau)$ as the ratio between the (time-varying) value of TA of each firm within each size/industry bin and the cutoff firm in that bin (see Appendix E for more details). This generates an index that we normalize between 0 (cutoff firms) and 1 (maximum financial capability).

Figure 1 reports the distribution of financial capability across firms and years. This gives us a good proxy of the heterogeneity of firms as regards the cost of finance. Different combinations of firms' size ranges (quintiles, deciles, twentiles) within industries, different TA cutoff levels (1%, 5%), and different industry aggregations (2-digit or 3-digit NACE level) produce different versions of the financial capability measure, which we will serve for sensitivity checks. Importantly for our identification strategy, the correlation between $\theta(\tau)$ and the standard measures of firm-level productivity (i.e. TFP or value added per employee) are not greater than .03 (Table D.2 in Appendix D, first column).

We have checked the plausibility of our indicator of financial capability comparing it with other variables used in the literature to gauge firms' ability to access external finance. Table 2 reports the conditional correlation of $\theta(\tau)$ with three different firm-year proxies of access to finance: the overall amount of firms' bank loans (in logs), as recorded on each firm's balance sheet; the ratio of interests on loans to the firm's operating revenues, with higher values indicating a better access; and the inverse of the ASCL index of financial

[20] We always identify our parameters by comparing firms operating within a given industry, at the 2 or 3-digit level of aggregation.

Figure 1: Distribution of $\theta(\tau)$ across firms and years



Note: Financial capability across deciles of firms' sales in each industry. Cutoff firms are those in the top 5% of Tangible Assets value in each size/industry partition. Financial capability is computed by taking ratio of each firm's TA to that of the cutoff firm, within every size/industry bin, and then bounding the index between 0 (cutoff firms) and 1 (maximum financial capability). More details on the computation are discussed in Appendix E.

constraints (Mulier et al., 2016), in which firm size, age, average cash flow level and average indebtedness are considered as drivers of access to external finance.[21] As we can see, controlling for year and firm-specific fixed effects, all regressions yield a positive and strongly significant correlation between our indicator of financial capability and other proxies of access to finance.

3.3 Estimation of productivity and markups

To estimate markups and productivity at firm level we start from De Loecker and Warzynski (2012, henceforth DLW), who estimate markups combining output elasticity with respect to an input with the share of the input expenditure on total sales. The DLW methodology is particularly suited for our estimation strategy for two reasons. First, it

[21]The index assigns a value of 0 or 1 for each variable/year depending on whether a firm is scoring below or above its industry median. In our measure a firm gets a score of 1 for age if the firm is older than the median, and 0 otherwise. Similar measures are constructed for a firm size, average ratio of cash flow to capital and average leverage ratio. The latter are calculated as averages over two years. Summing the four scores yields for each firm-year observation a score from 0 (constrained access to external finance) to 4 (unconstrained access).

Table 2: Robustness of $\theta(\tau)$ across firms and years

	(1)	(2)	(3)
Dependent variable	$\theta(\tau)_{i,t}$	$\theta(\tau)_{i,t}$	$\theta(\tau)_{i,t}$
$\text{Loan}_{i,t}$	0.0408***		
	(0.00243)		
Interest paid/operating $\text{revenue}_{i,t}$		0.0779***	
		(0.00364)	
$\text{ASCL}_{i,t}$			0.0219***
			(0.000980)
Obs.	89,011	65,186	80,319
R2	0.797	0.834	0.791
Firm FE	YES	YES	YES
Year FE	YES	YES	YES

Note: OLS estimation. Dependent variable: financial capability at the firm level (computed across deciles of sales, with firms having the top 5% of TA considered as the cutoff firms). *Loan* indicates firm's loans. *Interest paid/operating revenue* indicates the ratio between the two variables at the firm level. *ASCL* is the (inverse of the) original ASCL index of financial constraints by Mulier et al. (2016). All specifications are estimated with robust standard errors. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively.

obtains output elasticity from the estimation of a general production function, allowing for flexible technology and different sources of firm heterogeneity, as in our framework. Second, the correlation between the markup and firm characteristics is not affected by the use of real as against nominal (balance sheet) output data.[22]

Additional problems arise, however, when markups are estimated in a setting in which financial capability differs between firms. On the one hand, our proxy $\theta(\tau)$ is likely to be correlated with the (unobserved) firm-specific cost of capital. If the latter is not accounted for, this input price variation typically induces a downward bias in the estimated coefficients of the production function, from which markups are calculated. This issue is discussed in detail by De Loecker and Goldberg (2014). Moreover, the same idiosyncratic variation in the cost of capital would remain in the error term of the production function, and thus ultimately in our TFP estimates. This raises a potential problem of multicollinearity between TFP and financial capability when equation (11) is estimated structurally. For these reasons, we have modified the standard algorithms through which TFP is estimated.

[22]De Loecker and Warzynski (2012) discuss how, under a Cobb-Douglas technology, the output elasticity reduces to a constant, so that the bias induced by unobserved output prices affects only the estimated level of the markup, not its correlation with firm characteristics.

We start by estimating the production function as in Wooldridge (2009), which improves the methodology proposed by Ackerberg, Caves and Frazer (2015, henceforth ACF) and employed in De Loecker and Warzynski (2012). We then augment the set of regressors in the control function with our proxy for financial capability.[23] As a robustness check, we also estimate the production function using the ACF approach, both in its standard version (replicating the original DLW methodology), and again augmenting the control function with financial capability. The correlation at firm level between the different measures of TFP and our measure of financial capability remains in any case negligible (Table D.2 in Appendix D).

We then use the estimated production function coefficients to compute different measures of firm-level markups. Table 3 reports the median values and standard deviations of four different firm-level markups. The first two are markups estimated by the Wooldridge (2009) algorithm, both in the standard and the augmented version discussed above. The third measure is computed using production function coefficients estimated by the standard ACF routine, as in De Loecker and Warzynski (2012). The fourth measure is estimated via an ACF algorithm in which the control function is augmented with financial capability. We will employ these different measures to provide additional robustness checks of the model.

Table 3: Markup estimates: median values and standard deviations

Estimation method	Median	St. dev.
Wooldridge (standard)	1.2063	0.7543
Wooldridge (augmented)	1.2152	0.7066
ACF (standard)	1.0668	0.4016
ACF (augmented)	1.0886	0.6267

Note: Standard estimation follows Woolrdridge (2009) and Ackerberg, Caves and Frazer (2015). The augmented estimation introduces financial capability $\theta(\tau)$ in the control function.

One last potential problem with the DLW methodology is that it applies when the

[23] When firm-specific financial capability is not controlled for, we obtain an upward bias in the estimates of productivity, i.e. a downward bias in the estimated coefficients of the production function, in line with the effects hypothesized by De Loecker and Goldberg (2014).

input choices of firms are unconstrained, whereas their first-order condition could be biased when the constraint is binding. To verify how serious this problem might be in our sample, we have recalculated markups for our set of financially unconstrained firms. These are defined as firms that applied for and were granted additional credit from banks, or that did not apply for it. The markups estimated for these firms (using the Wooldridge standard algorithm) are not statistically different from the baseline presented in Table 3: median 1.2165, standard deviation 0.7572.

4 Empirical analysis

We estimate the markup equation (11) structurally at firm(i)-year(t) level; the dependent variable is markup estimated via DLW (2012). The covariates ωc_D and ϕ, which incorporate collateral requirement β, are fixed effects or controls (depending on specification), c is the inverse of our retrieved TFP measure at firm level and $\theta(\tau)$ is the cost advantage stemming from the heterogeneity of firms' financial capability, calculated as described in section 3.2. We test our markup equation for the years 2002-2013 under various specifications, plus several sensitivity and robustness checks. In addition, as heterogeneity in financial capability is relevant only for liquidity constrained firms, all the estimates are conditional on the firm's having used bank credit in order to satisfy its financing needs.[24]

Table 4 presents our benchmark results. The proxy for financial capability $\theta(\tau)$ is estimated by deciles of sales, and the cutoff level of tangible assets is set at the top 5% of the distribution for each size decile within each 2-digit NACE industry and year. Productivity and markups are estimated by the Woolridge (2009) algorithm, augmented to include financial capability. Column (1) includes a full set of firm fixed effects to neutralize any unobserved heterogeneity at firm level that could drive the results (such as firm-specific collateral requirements stemming from relationship lending), as well as year fixed effects. The results confirm the positive and significant correlation of markups with productivity. Further, even controlling for productivity and firm fixed effects, the more financially capable firms display significantly higher markups as the theoretical framework

[24] A total of 14,139 firms in our data, i.e. 96% of the sample, report the use of bank credit.

predicts. In column (2) we control for the possible impact of some financial or price shock occurring over time at certain firms (and thus not picked up by our firm FE); that is, we add, as a control, the change in collateral requirement at the country(c)-year(t) level, drawn from the ECB Bank Lending Survey.[25] While the coefficient of this variable is negative and significant (evidence that higher collateral requirements increase costs and thus reduce markups), our main results stand confirmed.

Table 4: Markups, productivity and financial capability

	(1) Within estimator	(2) Within estimator	(3) Between estimator	(4) Cross-section (OLS)
	all years	all years	all years	only 2008
Dependent variable	$\ln(\mu)_{i,t}$	$\ln(\mu)_{i,t}$	$\ln(\mu)_{i,t}$	$\ln(\mu)_{i,t}$
$\ln(TFP)_{i,t}$	1.547***	1.594***	1.363***	1.462***
	(0.0109)	(0.0139)	(0.0123)	(0.0191)
$\theta(\tau)_{i,t}$	0.437***	0.484***	0.205***	0.280***
	(0.0189)	(0.0231)	(0.0237)	(0.0375)
Δ collateral requirement$_{c,t}$		-0.0152*	-0.173*	
		(0.00778)	(0.101)	
Obs.	53,698	35,525	32,149	4,548
R2	0.807	0.836	0.726	0.769
Number of marks	7,873	7,249	6,544	
Firm size and age controls	NO	NO	YES	YES
Firm FE	YES	YES	NO	NO
Country-Industry FE	NO	NO	YES	YES
Year FE	YES	YES	YES	NO

Note: Dependent variable: $\ln(\mu)_{i,t}$ is the log of markups estimated as in De Loecker and Warzynski (2012). $\theta(\tau)_{i,t}$ indicates the cost advantage and is computed across deciles of sales, with firms at the top 5% of TA considered as the cutoff firms. $\ln(TFP)_{i,t}$ is the log of TFP, computed through the modified version of Wooldridge (2009), augmenting the control function with firm-level financial capability. *Change in collateral requirements* indicates the percentage increase/decrease in the collateral requirements by banks at country-year level. All specifications estimated with robust standard errors. ***,**,* = indicate significance at the 1%, 5%, and 10% level, respectively.

In the foregoing we have identified the effects of productivity and financial capability through the within variation in the data, implying that firms can adjust TA allocation, productivity and, consequently, markups over time. If our theory is valid, however, the results should hold also for the between variation in the data, i.e. across firms. Accordingly, columns (3) and (4) replicate the analysis of column (2) without firm fixed effects.

[25] The ECB Bank Lending Survey reports a large variation in collateral requirements by banks across euro area countries around the years 2008 and 2009: requirements tightened threefold on average in the euro area, but these effects were not similar in all countries. Chaney et al. (2012) find that shocks to the value of collateral (land prices in their case) can have a major impact on the value of the investment.

Column (3) uses a between estimator for the pooled sample of firms from 2002 to 2013; column (4) shows a simple OLS estimation on the cross-sectional variation for the year 2008, that is the year for which additional firm-level information from the Efige sample is available. We include a set of country×industry fixed effects to capture all possible spurious compositional effects other than firm-level variation. We also control for other firm characteristics that might be correlated with productivity and financial capability, notably firm's age and size.[26] In both cases the coefficient of financial capability decreases by around a third with respect to the within estimation, but still remains positive and highly significant.

Table 5 reports some sensitivity checks. We show the estimated coefficients of our two key variables, productivity and financial capability, in a number of different specifications. In a first battery of tests we keep the baseline (within) specification of Table 4, column (1) and change the estimation procedure of $\theta(\tau)$. That is, in row (1) we present results broadening the sales size ranges to quintiles and lowering the TA cutoff threshold of tangible assets to the top 10% of firms in each 2-digit NACE industry and year. In row (2) we do the opposite, calculating $\theta(\tau)$ by narrowing the size ranges of firms to twentiles, and raising the TA cutoff threshold to the top 1% in each industry-year. Rows from (3) to (5) replicate the three different estimation methods of Table 4 (FE, BE and OLS on the 2008 cross-section) with financial capability now measured within each 3-digit NACE industry (about 100 industries) and year. The sign and significance of our key parameters is always confirmed, with little change in magnitude compared with our benchmark.

A second group of sensitivity checks (rows 6 to 8) reverts to the benchmark measure of financial capability used in Table 4, while varying the method for estimating markups, so as to control for any spurious correlation deriving from the estimation method itself. Row (6) uses markups taken from production function coefficients estimated through ACF (2015), augmented for financial capability; row (7) replicates the results with markups

[26]Industry fixed-effects are taken from Manova (2013) as measures of financial vulnerability (i.e. the extent to which a firm relies on outside capital for investment). Firm size is controlled as a categorical variable, scoring from 1 to 4 for work force numbering, respectively, 10-19, 20-49, 50-249 and over 250 employees. The choice of a categorical variable reflects the need to reduce the possible endogeneity with TFP and other firm-specific controls. All our results are confirmed if we substitute the natural log of the number of employees for the size categories.

Table 5: Markups, productivity and financial capability - Sensitivity

	TFP		Financial Capability			
	Coeff	Std. Err.	Coeff	Std. Err.	Obs.	R2
Baseline (within)	1.547***	(0.0109)	0.437***	(0.0189)	53,698	0.807
(1) Quintile of sales, top 10% TA cutoff	1.587***	(0.0137)	0.390***	(0.0212)	35,525	0.835
(2) Twentiles of sales, top 1% TA cutoff	1.588***	(0.0138)	0.466***	(0.0256)	35,393	0.834
(3) Disaggregation at Nace 3 digits - FE	1.584***	(0.0142)	0.297***	(0.0190)	34,528	0.833
(4) Disaggregation at Nace 3 digits - BE	1.363***	(0.0123)	0.180***	(0.0198)	31,470	0.726
(5) Disaggregation at Nace 3 digits - Cross Section	1.450***	(0.0192)	0.223***	(0.0300)	4,459	0.769
(6) Markups ACF (augmented)	0.707***	(0.00922)	0.458***	(0.0201)	40,034	0.645
(7) Markups Wooldridge (standard)	1.575***	(0.0137)	1.283***	(0.0260)	35,565	0.825
(8) Markups ACF (standard)	1.585***	(0.0129)	0.655***	(0.0231)	39,777	0.836
Baseline (cross-section)	1.462***	(0.0191)	0.280***	(0.0375)	4,548	0.769
(9) Number of Banks	1.459***	(0.0188)	0.296***	(0.0367)	4,500	0.777
(10) R&D Investments	1.461***	(0.0191)	0.281***	(0.0375)	4,548	0.770
(11) Exporter Status	1.459***	(0.0191)	0.284***	(0.0372)	4,548	0.771
(12) N. of Banks, R&D Inv., and Exporter	1.457***	(0.0188)	0.299***	(0.0365)	4,500	0.778
(13) Only unconstrained firms	1.458***	(0.0200)	0.277***	(0.0389)	4,320	0.766

***,**,* = indicate significance at the 1%, 5%, and 10% level, respectively. Baseline values are from Table 4, column (1) (within) and column (4) (cross-section). All estimates with robust standard errors.

estimated from production function coefficients calculated via the standard algorithm of Woolridge (2009), i.e. not augmented for financial capability; row (8) repeats the exercise using standard ACF (2015) estimates, i.e. the original De Loecker and Warzynski (2012) measure. The sign and significance of our key parameters of TFP and financial capability are again confirmed, although the latter coefficient is significantly higher when using markup measures deriving from a production function estimation that does not correct ex-ante for the potential heterogeneity in firms' access to finance (columns 7 and 8).

Rows (9) to (12) of Table 5 serve to determine whether our specification remains significant also controlling for additional firm-level variables that are potentially correlated with financial capability and markups. To this end we use three questions from the Efige survey for 2008. The first is the number of banks used by the firm. The question is answered by practically the entire sample and gives a mean of three banks per firm and a median of two. The intuition here is that a firm that is better connected to more banks may well enjoy financial conditions that entail both lower cost of collateral (hence a higher $\theta(\tau)$), and the possibility of relatively higher markups (as losses would be covered by an extension of credit). If so, the correlation between financial capability and markup might be spuriously driven by this omitted variable. The second question we use relates to R&D investment. A firm could exploit its financial cost advantage to invest in R&D and innovation, thus either increasing physical productivity or enhancing product quality. Both these factors would produce higher revenue TFP and larger markups, again generating a spurious correlation with financial capability. The third characteristic observed in the data, which we control for in our cross-sectional estimates, is whether a firm has been consistently exporting part of its output. De Loecker and Warzynski (2012) indeed show that markups differ dramatically between exporters and non-exporters: they are statistically higher for exporting firms. At the same time, exporters might be able to raise collateral at lower cost. We control for each of these three characteristics in rows (9) to (11), respectively. In row (12) we run our benchmark specification considering number of banks, R&D and export status together. As these variables are only available for 2008, we use as a baseline the cross-sectional specification reported in column (4) of Table 4. All the main results are unchanged.

In row (13) we address the potential problem of constrained input choices potentially biasing production function coefficients when using the DLW methodology (see section 3.3). To that extent, we replicate our benchmark specification for the cross-sectional set of unconstrained firms (i.e. firms that either requested and obtained additional credit from banks, or did not apply for it). Once again, the sign and significance of our key parameters of TFP and financial capability remain unchanged.

As a further robustness check we seek to determine whether our results hold for alternative proxies of access to finance. This is relevant as the literature generally associates asset tangibility with the amount of collateral (e.g. Rampini and Viswanathan, 2013; Hengjie et al., 2018), and hence the volume of loans, rather than with its cost, as in our framework. Table 6 tests equation (11) with firm and year FE, comparing the results obtained estimating the markup equation using our proxy of financial capability (column 1, as in Table 4) with the three alternative proxies of firms' access to finance used in Table 2: the overall amount of bank loans (column 2); the ratio of loan interest payments to operating revenue (column 3); and the inverse of the ASCL index of financial constraints as in Mulier et al., 2016 (column 4). All four indicators are positive and significant, indi-

Table 6: Markups, productivity and financial capability - Robustness

	(1)	(2)	(3)	(4)
Dependent variable	$\ln(\mu)_{i,t}$	$\ln(\mu)_{i,t}$	$\ln(\mu)_{i,t}$	$\ln(\mu)_{i,t}$
$\ln(TFP)_{i,t}$	1.547***	1.526***	1.579***	1.504***
	(0.0109)	(0.0115)	(0.0129)	(0.00952)
$\theta(\tau)_{i,t}$	0.437***			
	(0.0189)			
$\text{Loan}_{i,t}$		0.0238***		
		(0.00541)		
Interest paid/operating $\text{revenue}_{i,t}$			0.0353***	
			(0.00841)	
$\text{ASCL}_{i,t}$				0.0359***
				(0.00226)
Obs.	53,698	50,828	41,841	47,551
R2	0.807	0.795	0.819	0.801
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Note: Dependent variable: $\ln(\mu)_{i,t}$ is the log of markups estimated as in De Loecker and Warzynski (2012), using production function coefficients estimated as in Wooldridge (2009). $\theta(\tau)_{i,t}$ indicates the cost advantage and is computed across deciles of sales, with firms having the top 5% of TA as cutoff. $\ln(TFP)_{i,t}$ is the log of TFP, computed through a modified version of Wooldridge (2009), cleaning production function estimates for firm-level financial capability. *Loan* indicates firm's loans. *Interest paid/operating revenue* indicates the ratio between the two variables at firm level. *ASCL* is the ASCL-index by Mulier et al. (2016). All estimates employ robust standard errors. ***,**,* = indicate significance at the 1%, 5%, and 10% level, respectively.

cating that heterogeneity in access to finance, however measured, can help explaining the dispersion of markups across firms in addition to productivity.

5 Financial frictions and economic shocks

We now extend our framework to the aggregate industry equilibrium, in order to analyze the effects of economic shocks and the role of financial frictions in the adjustment process. The free entry condition at the industry level establishes that expected profits are equal to the fixed cost of entry f_E.[27] Using the notation of our model, this can be written as:

$$\pi^e(c,\tau) = \frac{Lk}{4\gamma c_M^k} \int_0^{c_D} \int_a^1 \left[\omega c_D - c - \phi + \theta(\tau)\right]^2 c^{k-1}\, d\tau\, dc = f_E$$

[27] Appendix B characterizes the industry equilibrium under the assumption of a uniform distribution of firms' ability τ, with density equal to $f(\tau) = \frac{1}{1-a}$. This implies that the cutoff $\tilde{\tau}$ does not vary with the primitives of the model, whereas the industry cost cutoff c_D is a function of the distribution of surviving firms' productivity. This simplification maintains our assumption of heterogeneity in firms' access to finance, while singling out the role of collateral requirements (the other component of financial frictions) in driving the industry equilibrium. However, introducing a non-uniform distribution of financial capability, and thus an endogenous financial capability cutoff, it can be shown that a shock (e.g. a change in market size) would affect both the financial capability and the production cost cutoffs in the same direction. As a result the effect of financial frictions on the industry equilibrium would be similar.

From here we can derive an expression for the average markup, which corresponds to:

$$\overline{\mu} = \frac{1}{2}\frac{\int_0^{c_D}\int_a^1 \left[\omega c_D - c - \phi + \theta(\tau)\right] f(\tau)g(c)dcd\tau}{G(c_D)F(1-a)}$$

Solving the integral yields:

$$\overline{\mu} = \frac{1}{2}\left[\frac{\omega k + \omega - k}{k+1}c_D - \beta\psi\right] \tag{12}$$

with $\psi > 0$ a constant that depends on the exogenous parameters of the model.

In order to analyze the effects of an economic shock on the average markup, we consider the effects of a change in market size L. Differentiating equation (12) gives:

$$\frac{\partial\overline{\mu}}{\partial L} = \frac{1}{2}\left[\frac{\omega k + \omega - k}{k+1}\frac{\partial c_D}{\partial L}\right]$$

As it is shown in Appendix C, we have $\partial c_D/\partial L < 0$, and hence $\partial\overline{\mu}/\partial L < 0$; that is, an increase in market size tends to reduce the average industry markup by lowering the cost cutoff, in line with the pro-competitive effects identified in the literature. Financial frictions, however, do affect the economy's reaction to the shock: Appendix C also shows, in fact, that the magnitude of the derivative of the cost cutoff with respect to L depends, among other things, on the amount of collateral requirement β. In particular, when β is relatively large, i.e. when banks require more collateral for the same loan, *ceteris paribus* the effect of a change in L on the cost cutoff is smaller (see Appendix C for a formal discussion). In other words, while we still find that an increase in market size induces pro-competitive effects on the average industry markup, we can also see that the extent of the pass-through is mediated by the level of collateral requirements.

In order to test this result, we can exploit the sharp and symmetric collapse of exports by European countries during the credit crisis of late 2008 / early 2009 (Baldwin, 2009). In our framework, this can be considered as a natural experiment in which a negative demand shock (a decrease in L) is associated with an increase in collateral requirements (an increase in β).[28] Since our goal is now to determine the average effect of collateral requirements on firm-level markups, controlling for productivity and financial capability, we need to exploit variation across firms in both markups and collateral requirements.

To this end, we again start from the estimation of equation (11) for each industry, including firm and time fixed effects. The normalized residuals of this regression can be interpreted as the deviation of the specific firm-year markup from the industry-wide average, controlling for firm-specific productivity and financial capability. This residual, which we denote $\beta_{i,t}$, proxies for the tightness of collateral requirements at the firm level, which we can exploit for identification.[29] Appendix D shows the weak correlation of our proxy with other regressors of the model, notably financial capability and TFP. In Appendix F we run a plausibility check of $\beta_{i,t}$. As the latter is a proxy of the tightness of collateral requirements, we regress it against other variables related to firm's financial constraints widely cited in the literature, in particular the indexes of Whited and Wu (2006) and Hadlock and Pierce (2010), always controlling for firm and year fixed effects. Reassuringly, our proxy appears to be positively and significantly correlated with these two indexes. We also regress our measure against firms' sales volume: this yields negative and significant coefficients, in line with the assumption of Gopinath et al. (2017) that credit constraints are size-dependent, with larger firms experiencing relatively less tight collateral requirements.

Once we have established a plausible proxy of collateral requirements across firms, we use BACI trade data at country-industry-year level and create for each industry z a dummy variable $NTS_{z,ct} = 1$ if the yearly growth of a given export flow in industry z in each country-year ct is in the bottom 25% of the distribution of export growth rates.

Our theoretical model predicts that $\partial\overline{\mu}/\partial L < 0$, i.e. an increase in market size lowers the average industry markup, in line with the pro-competitive effects cited in the litera-

[28] As noted, the ECB Bank Lending Survey reports a threefold increase in collateral requirements by banks in the euro-area countries around the years 2008 and 2009, a factor that we have controlled for in our estimations of financial capability in Table 4.

[29] Recall that we estimate equation (11) structurally under the assumption of an industry-specific amount of collateral per unit of output β equal across firms. If the latter varies across firms and years, i.e. if the (unobservable) amount of collateral per unit of output required by banks is $\beta_{i,t}$, this should be incorporated in the residuals of the estimation.

ture. As a result, regressing markups on our negative trade shock dummy $NTS_{z,ct}$ should produce positive coefficients, as firms operating in industries experiencing significantly lower exports (smaller market size) should react setting higher markups. Our theoretical setting also suggests a negative sign for the collateral requirement $\beta_{i,t}$: with a stiffer requirement, some firms would be unable to satisfy the liquidity constraint as the repayment $R(c)$ increases. Hence, the least efficient firms (in terms of production costs) would exit the market, driving down the production cost cutoff c_D, and thus lowering markups. Crucially, we should also observe a negative sign of the interaction between the economic shock and the collateral requirement $\beta_{i,t} \times NTS_{z,ct}$, as our theoretical model indicates that the derivative $\partial\overline{\mu}/\partial L$ should become smaller, the higher the collateral requirement.

Table 7 reports the results of our reduced-form estimation for the period 2006-2009, embracing the 2008/09 shock.[30] Since we are testing for an effect on the average industry markup, we use a pooled OLS estimation. Consistent with our previous findings, we always control for productivity and financial capability at firm level. We also add controls for credit market developments in a given country×year (bank credit/GDP and non-performing loans in the bank sector/GDP, from Eurostat), industry and year fixed effects, as well as individual time-varying firm characteristics (age and size). We always employ bootstrapped standard errors, given that we use an estimated proxy for collateral requirements across firms.

In column (1), markups, TFP and financial capability are defined as in our benchmark specification. The results are in line with our priors: TFP and financial capability have the expected sign and significance, and a negative economic shock raises markups significantly, while higher collateral requirements lower them. Most importantly, the interaction between the economic shock and the collateral requirement is negative and significant. Columns (2) to (5) report sensitivity checks. In column (2) we use the measure of financial capability estimated at the 3-digit NACE level. In column (3) financial capability is retrieved by enlarging the size range of sales to quintiles and lowering the TA cutoff threshold to the top 10% of firms in each 2-digit NACE industry and year.

[30]We obtain similar results for the period 2007-2010.

Table 7: Financial frictions and economic shocks

	(1)	(2)	(3)	(4)	(5)
	decile of sales, top 5% TA cutoff	decile of sales, top 5% TA cut-off, Nace 3 digits	quintile of sales, top 10% TA cut-off	decile of sales, top 5% TA cutoff	decile of sales, top 5% TA cutoff
	Firm-specific $\beta_{i,t}$	Firm-specific $\beta_{i,t}$	Firm-specific $\beta_{i,t}$	Firm-specific $\beta_{i,t}$	$\beta_{i,t}$ above/below median
Dependent variable	$\ln(\mu)_{i,t}$ Wooldridge (augmented)	$\ln(\mu)_{i,t}$ Wooldridge (augmented)	$\ln(\mu)_{i,t}$ Wooldridge (augmented)	$\ln(\mu)_{i,t}$ ACF (augmented)	$\ln(\mu)_{i,t}$ Wooldridge (augmented)
$\ln(TFP)_{i,t}$	1.362***	1.360***	1.361***	1.205***	1.366***
	(0.0137)	(0.0138)	(0.0132)	(0.0176)	(0.0132)
$\theta(\tau)_{i,t}$	0.222***	0.188***	0.209***	0.204***	0.224***
	(0.0278)	(0.0229)	(0.0252)	(0.0300)	(0.0287)
$\beta_{i,t}$	-0.585***	-0.593***	-0.585***	-0.338***	-0.143***
	(0.0467)	(0.0503)	(0.0477)	(0.0552)	(0.0113)
$NTS_{z,ct}$	0.422***	0.415***	0.421***	0.518***	0.408***
	(0.0793)	(0.0870)	(0.0858)	(0.0897)	(0.0741)
$\beta_{i,t} \times NTS_{z,ct}$	-0.192**	-0.168*	-0.195**	-0.443***	-0.114***
	(0.0947)	(0.101)	(0.0936)	(0.101)	(0.0279)
Obs.	13,126	12,853	13,126	12,466	13,126
R2	0.757	0.757	0.757	0.672	0.754
Number of marks	5,794	5,681	5,794	5,516	5,794
Firm size and age controls	YES	YES	YES	YES	YES
Country-Year controls	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Bootstrapped (1000) SE	YES	YES	YES	YES	YES

Notes: Dependent variable: $\ln(\mu)_{i,t}$ is the log of markups estimated as in De Loecker and Warzynski (2012). $\theta(\tau)_{i,t}$ indicates the firm-specific cost advantage, computed by decile of sales, taking firms in the top 5% of TA as cutoff firms in columns 1, 2, 3, 5, and 10% in column 4. $\ln(TFP)_{i,t}$ indicates the log of TFP, computed through the augmented version of Wooldridge (2009), cleaning production function estimates for firm-level financial capability in columns 1, 2, 3, 5, and the similarly augmented version of Ackerberg, Caves and Frazer (2015) in columns 4. $NTS_{z,ct}$ is a dummy variable for a negative economic shock, assuming value 1 if the yearly growth of a given export flow in industry z in a country×year is in the bottom 25% of the overall distribution of export growth rates. $\beta_{i,t}$ indicates firm-level variation in collateral requirement, proxied by the residual of the estimation of equation (11). All specifications estimated with bootstrapped standard errors (1,000 reps). ***,**,* = indicate significance at the 1%, 5%, and 10% level, respectively.

In column (4), the dependent variable is the markup estimated through the augmented ACF (2015) algorithm. Finally, in column (5) we measure firm-level variation in collateral requirement by a dummy taking value 1 for firms above the median estimated $\beta_{i,t}$. All our results remain consistent with our theoretical priors.

6 Conclusions

In this paper we have investigated firm-specific financial frictions in a framework of monopolistically competitive firms with heterogeneous productivity and endogenous markups (as in Melitz and Ottaviano, 2008, among others). Specifically, before producing firms have to pledge collateral (tangible assets) in order to obtain a bank loan to cover part of their production costs. Firms are heterogeneous not only in productivity, but also in their cost of accessing finance: the cost of raising collateral is lower for some firms, a feature that we define as financial capability. Having obtained the loan, firms enter the market and set profit maximizing prices and markups, given their specific productivity and financial capability. The main implication of our framework is that financial capability (the firm's relative cost advantage in raising collateral) and the amount of collateral required figure, together with productivity, in the equilibrium expressions of firms' prices and markups.

Our theoretical results are validated for a representative sample of manufacturing firms in seven European countries during the financial crisis. Guided by theory, we estimate the financial capability, TFP and markup of each firm. In our framework, all the firm-specific parameters can be estimated using balance-sheet data. The empirical estimates confirm the model's implications, and are robust to a battery of sensitivity checks as well as to other (reduced-form) proxies of access to finance commonly used in the literature.

Our paper sheds light on the different channels through which financial frictions can affect the industry equilibrium. Both theoretically and empirically, our model shows that for any given level of collateral requirement and productivity, the more financially capable firms do not translate their entire financing cost advantage into lower prices, but instead retain relatively higher margins in equilibrium. This result implies that heterogeneity in access to finance explains part of the observed dispersion of prices and markups across firms, even after controlling for productivity and size. An implication of this finding is that shocks that influence asset tangibility (e.g. technological shocks), and thus condition their potential use as collateral, should affect the industry equilibrium also in terms of markup dispersion, in addition to the effects they generate on productivity.

Extending our model to the aggregate industry equilibrium, we find, again both theoretically and empirically, that for any given level of firms' financial capability, and hence ex-ante dispersion of markups, the amount of collateral requirement attenuates the aggregate pass-through induced by demand shocks. In other words, the extent of the pro-competitive adjustments of industries is also a function of the amount of credit available to firms. As a result, episodes of economic liberalization that take place in contexts of relatively inefficient bank systems or, worse, that endogenously generate a relatively tighter access to credit by firms, are likely to deliver much lower pro-competitive effects with respect to a situation in which financial constraints are relatively mild. The latter represent, we believe, an important caveat in the design of future structural policies of economic liberalization.

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A The microfoundation of financial capability

We provide a microfoundation of financial capability $\theta(\tau)$. In order to produce, firms combine redeployable (Re) and non-redeployable (NRe) assets using a generic CES aggregator of the form $\left(\delta Re^{\frac{\sigma-1}{\sigma}} + (1-\delta)NRe^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$, with $\delta \in (0,1)$ and $\sigma > 1$ being respectively the input share of Re assets and the elasticity of substitution between the latter and NRe assets. These are exogenous parameters fixed by industry-specific technology: certain industries require the use of relatively more redeployable assets (e.g. land) than others (higher δ), or allow for greater substitutability between Re and NRe assets (different σ). As firms are required by banks to pledge β units of tangible assets per unit of output, the technological constraint for a firm that intends to produce is

$$\left(\delta Re^{\frac{\sigma-1}{\sigma}} + (1-\delta)NRe^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} = \beta \tag{A.1}$$

We posit that a firm with ability $\tau \in [0,1]$ is able to lower the requirement of redeployable assets by $1-\epsilon(\tau)$ units, with $\epsilon(\tau) \geq 0$ and strictly increasing in τ.[31] Given the technological constraint, the marginal cost of collateral, computed for the optimal amount of redeployable and non-redeployable assets is then

$$C(\tau) = \frac{\beta\left(1-\epsilon(\tau)\right)}{\left[\delta^{\sigma} + (1-\delta)^{\sigma}\left(1-\epsilon(\tau)\right)^{\sigma-1}\right]^{\frac{1}{\sigma-1}}} \tag{A.2}$$

in which $C(\tau)$ is strictly decreasing in τ. The financial ability cutoff $\widetilde{\tau}$ is such that $\epsilon(\widetilde{\tau}) = 0$: a firm with the (cutoff) ability $\widetilde{\tau}$ obtains no advantage in the price of redeployable assets, which constitutes the upper bound on the marginal cost of collateral; substituting $\widetilde{\tau}$ in Equation (A.2), this is equal to:

$$C(\widetilde{\tau}) = \beta\left[\delta^{\sigma} + (1-\delta)^{\sigma}\right]^{-\frac{1}{\sigma-1}} \tag{A.3}$$

[31] Guner et al. (2008) find that the financial expertise of directors plays a positive role in firms' investment policies. Glode et al. (2012) model financial expertise as a skill in estimating the value of securities, showing how this characteristic increases firms' ability to raise capital.

Subtracting (A.2) from (A.3) we get:

$$\theta(\tau) = C(\widetilde{\tau}) - C(\tau) = \beta[\nu(1 - \eta(\tau))] \tag{A.4}$$

with $\eta(\tau) = [(1 - \epsilon(\tau))^{\sigma-1}]^{-\frac{1}{\sigma-1}}$ and $\nu = [\delta^{\sigma} + (1 - \delta)^{\sigma}]^{-\frac{1}{\sigma-1}}$ both constant and positive terms. Given the exogenous parameters, Equation (A.4) is increasing in τ and describes the cost advantage in raising collateral that a firm with financial capability τ has vis-à-vis the cutoff firm - that is, the former's financial capability. It is easily seen that the financial capability cutoff firm characterized by $\epsilon(\widetilde{\tau}) = 0$ has no cost advantage, i.e. $\theta(\widetilde{\tau}) = 0$.

B Existence and uniqueness of cost cutoff c_D

The marginal cost of production c follows an inverse Pareto distribution (as in Melitz and Ottaviano, 2008), with a shape parameter $k \geq 1$ over the support $[0, c_M]$. The cumulative density function can then be written as:

$$G(c) = \left(\frac{c}{c_M}\right)^k \quad \text{with} \quad c \in [0, c_M]$$

The density function is $g(c) = \frac{kc^{k-1}}{c_M^k}$ while the distribution of surviving firms, once productivity has been drawn, is still an inverse Pareto with density equal to $g(c) = \frac{kc^{k-1}}{c_D^k}$. From the equations of demand and supply we can derive an expression for a firm's profits in equilibrium:

$$\pi(c, \tau) = \frac{L}{4\gamma}\left[\omega c_D - c - \phi + \theta(\tau)\right]^2 \tag{B.1}$$

A (c, τ)-firm would be willing to enter the market up to the point where expected profits are equal to the fixed cost of entry f_E, i.e.:

$$\pi^e(c, \tau) = \int\int \frac{L}{4\gamma}\left[\omega c_D - c - \phi + \theta(\tau)\right]^2 \, dF(\tau)\, dG(c) = f_E \tag{B.2}$$

To solve the integral, we assume that τ follows a uniform distribution with $\widetilde{\tau} = a$ and $a \in [0, 1)$. The distribution of surviving firms, once financial capability has been drawn, is then still uniform with density equal to $f(\tau) = \frac{1}{1-a}$. Since $dG(c) = g(c)dc$ and $dF(\tau) = f(\tau)d\tau$, we can then rewrite the integral as:

$$\pi^e(c, \tau) = \frac{Lk}{4\gamma c_M^k}\int_0^{c_D}\int_a^1 \left[\omega c_D - c - \phi + \theta(\tau)\right]^2 c^{k-1}\, d\tau\, dc = f_E \tag{B.3}$$

Solving the integral yields

$$\pi^e = \frac{Lk}{4\gamma c_M^k} c_D^k \left[A c_D^2 + B c_D + C\right] = f_E$$

with the terms A, B and C respectively equal to:

$$A = (1-a)\left[\frac{1}{2+k} - \frac{2\omega}{1+k} + \frac{\omega^2}{k}\right]$$

$$B = \frac{2(\omega + k\omega - k)\left[(a-1)(\delta-1)^2(\phi(1+2\delta^2-2\delta)-\beta) + \beta(1+2\delta^2-2\delta)ln\left(\frac{\delta^2+a(\delta-1)^2}{1+2\delta^2-2\delta}\right)\right]}{k(1+k)(\delta-1)^2(1+2\delta^2-2\delta)}$$

$$C = \frac{1}{k}\frac{\beta^2(\delta-1)^4}{(1+2\delta^2-2\delta)^2}$$
$$\left[\frac{(1-a)(1+a-2\delta(1+a)+(3+a)\delta^2)}{(\delta-1)^4(\delta^2+a(\delta-1)^2)} - \frac{2(1+2\delta^2-2\delta)\ln\left(\frac{1+2\delta^2-2\delta}{\delta^2+a(\delta-1)^2}\right)}{(\delta-1)^6}\right]$$
$$+\frac{\phi^2(1-a)}{k} + \frac{2\beta\phi\ln\left(\frac{1+2\delta^2-2\delta}{\delta^2+a(\delta-1)^2}\right)}{k(\delta-1)^2} - \frac{2(1-a)\beta\phi}{k(1+2\delta^2-2\delta)}$$

Now define $f(c_D)$ as:

$$f(c_D) = \pi^e - f_E = Ac_D^{k+2} + Bc_D^{k+1} + Cc_D^k - \frac{4f_E\gamma c_M^k}{Lk}$$

By Rolle's Theorem, between two solutions for $f(c_D) = 0$ there is always a solution for $f'(c_D) = 0$. Hence if $f'(c_D) = 0$ can be shown to exist, then there also exist at least two positive values of the cost cutoff, as $c \in [0, c_M]$. And as long as the second positive cost cutoff is $> c_M$, this also implies the uniqueness of c_D. By taking the first derivative of $f(c_D)$ we obtain

$$f'(c_D) = (k+2)Ac_D^{k+1} + (k+1)Bc_D^k + kCc_D^{k-1}$$

where $A > 0$ and $C > 0$ always, while $B < 0$. Hence, by Descartes' Rule, $f'(c_D) = 0$ has at least two positive solutions, i.e. there is a solution to $f(c_D) = 0$, which implies that there always exists a positive solution for c_D and that it is unique conditional on a choice of c_M.

C Derivative of the cost cutoff with respect to L

Differentiating equation (12) gives

$$\frac{\partial \overline{\mu}}{\partial L} = \frac{1}{2}\left[\frac{\omega k + \omega - k}{k+1}\frac{\partial c_D}{\partial L}\right]$$

Applying Dini's implicit function theorem, we obtain:

$$\frac{\partial c_D}{\partial L} = -\frac{\partial \pi^e(L, c_D(L))/\partial L}{\partial \pi^e(L, c_D(L))/\partial c_D}$$

The derivative of the expected profit function with respect to L (the numerator of the above expression) is equal to:

$$\frac{\partial \pi^e(L, c_D(L))}{\partial L} = \frac{k c_D^k}{4\gamma c_M^k}(A c_D^2 + B c_D + C) > 0$$

with A, B and C as defined in Appendix B. The denominator is instead equal to:

$$\frac{\partial \pi^e(L, c_D(\beta))}{\partial c_D} = \frac{L k c_D^{k-1}}{4\gamma c_M^k}[(k+2)A c_D^2 + (k+1)B c_D + kC] > 0$$

Hence, we have that:

$$\frac{\partial c_D}{\partial L} = -\frac{\partial \pi^e(L, c_D(L))/\partial L}{\partial \pi^e(L, c_D(L))/\partial c_D} < 0$$

Considering how collateral requirements affect the above derivative, we must assess how changes in β affect the terms B and C, where β is present. Numerical computations show that higher β translates, *ceteris paribus*, into lower $\frac{\partial c_D}{\partial L}$, for a very broad range of the exogenous parameters considered in the model.

D Descriptive statistics

Table D.1: Descriptive statistics

	Obs.	Mean	Std. Dev.	Min	Max
Tangible fixed assets	139,119	1,800	4,551	1	50,224
Sales	115,151	10,197	23,940	185	250,391
Number of employees	102,841	65	112	10	1,063
$\theta(\tau)$	104,590	0.330	0.189	0	1
Loan	101,147	0.590	0.381	0	1
Interest paid / operating revenue	68,983	0.381	0.370	0	1
ASCL	90,158	1.844	1.029	0	4
Δ collateral requirement	93,912	0.102	0.158	0	1
Employees (categorical)	191,503	2.019	0.890	1	4
$\ln(Age)$	191,425	3.399	0.705	1	6
β_i	47,536	0.492	0.142	0	1
NTS	57,352	0.250	0.433	0	1
Number of banks	14,571	2.99	2.02	1	14
Investments in R&D	14,759	0.60	0.49	0	1

Table D.3: Correlations of right-hand side variables

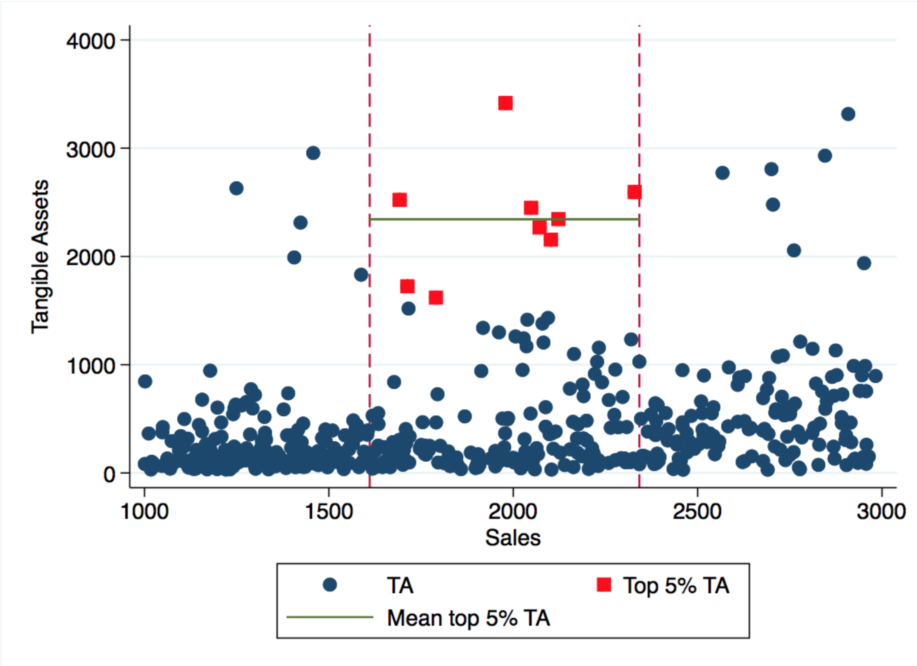
	$\theta(\tau)_{i,t}$	$\ln(TFP)_{i,t}$ Wooldridge not corrected	$\ln(TFP)_{i,t}$ Wooldridge corrected	$\beta_{i,t}$	Value added per employee$_{i,t}$	Total asset$_{i,t}$
$\theta(\tau)_{i,t}$	1					
$\ln(TFP)_{i,t}$ Wooldridge (standard)	0.0316	1				
$\ln(TFP)_{i,t}$ Wooldridge (augmented)	-0.0651	0.4674	1			
$\beta_{i,t}$	-0.0086	-0.0001	0.013	1		
Value added per employee$_{i,t}$	0.0307	0.3215	0.265	-0.0464	1	
Total asset$_{i,t}$	-0.2342	0.1099	0.1488	-0.0191	0.2871	1

Notes: $\theta(\tau)$ is financial capability estimated as in section 3.1; $\ln(TFP)_{i,t}$ is total factor productivity estimated as in Wooldridge(2009) both in the standard and the augmented version as discussed in section 3.2; β_i is the firm-specific proxy for collateral requirements, estimated as discussed in section 5.

E Estimation of financial capability $\theta(\tau)$

In this section we provide a graphical representation of the procedure adopted to estimate our measure of financial capability $\theta(\tau)$.

Figure E.1: Example of $\theta(\tau)$ estimation



Note: The dashed vertical lines enclose the 4^{th} decile of firms by size (sales) of the French food industry. The dots represent each firm's tangible assets. The squares represent, within the 4^{th} decile of sales, firms in the top 5% of TA value (cutoff firms). The solid horizontal line indicates the mean value of TA for the cutoff firms.

1. We create bins of firms of the same size within each industry: in the figure each blue dot represents the value of the tangible assets of each firm, and the dashed vertical lines delimit the 4^{th} decile of firms by size (measured by sales).

2. For each size bin (area within the vertical dashed lines), we identify as cutoff firms those with the highest TA (the squares in the figure) and compute their average value (solid horizontal line).

3. We compute firm-year financial capability $\theta(\tau)$ as the ratio of the (time-varying) value of TA of each firm within each size/industry bin (each blue dot) to that of the cutoff firm(s) in the same partition (solid horizontal line).

4. We re-scale this index from 0 (cutoff firms) to 1 (maximum financial capability).

F Firm-level variation of the collateral requirement

This section presents the results of the plausibility check of $\beta_{i,t}$. Table F.1 compares and correlates our measure $\beta_{i,t}$ with the indexes of Whited and Wu (2006) and Hadlock and Pierce (2010), and with firms' *sales* (measured in log).

Table F.1: Plausibility check of $\beta_{i,t}$

	(1)	(2)	(3)
Dependent variable	$\beta_{i,t}$	$\beta_{i,t}$	$\beta_{i,t}$
$\text{WW}_{i,t}$	0.0440***		
	(0.00167)		
$\text{HP}_{i,t}$		0.0233***	
		(0.00189)	
$\ln(sales)_{i,t}$			-0.0492***
			(0.00553)
Obs.	43,805	46,912	47,079
R2	0.760	0.999	0.074
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Robust SE	YES	YES	YES

Note: Dependent variables: ; $WW_{i,t}$ indicates the Whited and Wu index of credit constraints (2006);$HP_{i,t}$ is the Hadlock and Pierce index of credit constraints (2010); $\ln(sales)_{i,t}$ is log of firms' sales. ***,**,* = indicate significance at the 1%, 5%, and 10% level, respectively.