Markups, Productivity and the Financial Capability of Firms*

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Abstract

We incorporate the presence of financial frictions in a framework of monopolistically competitive firms with endogenous markups. Before producing, firms need to obtain a loan necessary to cover part of production costs, for which they have to pledge collateral in the form of tangible assets. Firms are heterogeneous in both productivity and access to finance: some firms have access to collateral at lower costs. As a result, financial capability and collateral requirements enter, together with productivity, in the expression of the equilibrium markup at the firm level. At the aggregate level, our framework shows that financial frictions in the form of higher collateral requirements mitigate the pro-competitive outcome of economic liberalization via the effects they have on the pass-through of shocks to prices. We validate our theoretical results capitalizing on a representative sample of manufacturing firms surveyed across a subset of European countries during the financial crisis. Guided by theory, we estimate for each firm financial capability, TFP and markups. We then employ those estimates to structurally retrieve from the model a measure of the collateral requirements faced by each firm (a proxy of firm-level credit constraints), and test our main propositions.

Keywords: Financial frictions, heterogeneous firms, markups

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1 Introduction

A large and growing literature shows how financial market frictions affect economic outcomes through their interplay with firms' characteristics. In particular, credit constraints have been recognized as an important determinant of export or innovation activity, on top of firms' productivity.[1] Financial frictions have also been shown to influence the allocation of capital across firms, and thus aggregate productivity (Gopinath et al., 2017; Larrain and Stumpner, 2017). Most of the models developed by this literature, however, assume CES preferences, and thus abstract away from the competitive effects induced on the economic equilibrium by endogenous markups. This is because in CES models the pass-through of financial shocks on prices is complete. Still, a growing evidence points at a distribution of firm-level markups that tends to be dispersed rather than concentrated at a single value (Atkin et al., 2015; De Loecker et al., 2016; Mrázová et al., 2017). In addition, empirical evidence points at the fact that firms, on top of productivity and markups, are also highly heterogeneous in their access to external finance.[2]

Motivated by these findings, this paper incorporates financial frictions in a framework in which firms are heterogeneous in both productivity, access to finance and markups. Specifically, before producing firms need to access collateral in the form of tangible assets. Collateral is required by banks in order to provide a loan necessary to cover part of the firm's production costs. Once the loan is obtained, firms set profit maximizing prices, given their specific productivity. To account for the heterogeneous access of firms to external finance, firms differ not only in productivity, but also in their financial capability, i.e. different firms require a different volume of loans and access collateral at different costs.

[1]See among others Minetti and Zhu (2011); Gorodnichenko and Schnitzer (2013); Manova (2013); Peters and Schnitzer (2015); Muuls (2015).

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

The main implication of our framework is that financial capability (the cost of collateral for firms) and collateral requirements (the quantity of collateral requested by banks) enter, together with productivity, in the equilibrium expressions of firm's prices and markups. At the individual firm level our model shows that, for any given level of collateral requirement and productivity, more financially capable firms do not transfer all their financing cost advantage into lower prices, but rather retain relatively higher margins in equilibrium. This result implies that heterogeneity in access to finance can explain part of the dispersion of prices and markups observed across firms in the data, even after controlling for productivity and size. A second result shows that, for any given distribution of financial capability across firms, higher collateral requirements requested by banks (a proxy of credit constraints) tend to mitigate the pro-competitive effects typically induced by positive demand shocks at the industry level. The latter result implies that the presence of financial frictions can affect the aggregate pass-through effects taking place in episodes of economic liberalization, with important consequences in terms of welfare.

These two novel theoretical results are tested empirically on a large representative sample of manufacturing firms surveyed across seven European countries during the financial crisis (the Efige dataset).[3] The cross-country nature of our data allows us to draw conclusions that do not depend on specific institutional features of individual countries. For each firm in the Efige survey we have balance-sheet data from 2002 to 2013, an information retrieved using the Amadeus database managed by Bureau van Dijk. The latter allows us to retrieve a number of indicators on individual firms' performance as well as financial structure. Through the survey we also have access to a number of additional firm-specific characteristics, typically unobserved in balance sheet (e.g. innovation activities, firm-bank relationship), that we use to assess the robustness of our results.

[3]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 across the following countries: Austria, France, Germany, Hungary, Italy, Spain, and the United Kingdom.

Specifically, guided by our model we retrieve from balance sheet data a non-parametric measure of the financial capability characterizing each firm. We then estimate a firm-level measure of total factor productivity (TFP) purged from the effect of financial capability, and use it to compute firm-specific markups along the methodology proposed by De Loecker and Warzynski (2012).[4] Finally, we use the estimated financial capability, TFP and markups to structurally back out from the model a firm-specific measure of collateral requirement (a proxy of credit constraints now measured at the firm level), and test our theoretical propositions. Empirical estimates confirm the theoretical insights of the model, and are robust to a battery of sensitivity and robustness checks. The structurally estimated firm-level measure of collateral requirement can be retrieved from our framework using simple balance sheet data, and performs in line with other proxies of credit constraints measured at the firm-level currently employed in the literature. The latter is an additional empirical contribution of this paper.

The theoretical model draws a number of insights from the financial literature. In order to provide a micro-founded channel for the heterogeneity of firms in their access to finance, we exploit the fact that tangible assets have a different level of 'redeployability' (Berger et al., 2011; Campello and Giambona, 2013; Cerqueiro et al., 2016). The idea is that more redeployable tangible assets (e.g. land) are less firm-specific, but can be more easily sold and thus are more easily accepted as collateral. We also exploit evidence that a larger firm size is typically associated to higher loans (Rampini and Viswanathan, 2013). As more productive firms have a larger size in equilibrium, in our framework they request higher loans to finance production and thus require more collateral. In turn, more financially capable firms obtain

[4] We employ a modified version of the routine for markup estimation proposed by De Loecker and Warzynski (2012). The latter relies on a control function for unobserved productivity and allows for flexible production technologies, being able to accommodate a different range of (dynamic or fixed) inputs of production. As in our model more financially capable firms are able to obtain fixed assets at cheaper costs, in order to obtain unbiased productivity and markup estimates at the firm-level we have modified the standard algorithms of TFP estimation (Woolridge, 2009 or Ackerberg et al., 2015) incorporating a control for the effects of financial capability.

redeployable assets which they can use as collateral at lower prices, and thus benefit from lower financing costs.

The paper is also related to a recent literature that looks at the implications of financial frictions for capital allocation and productivity. Larrain and Stumpner (2017) develop a multi-sector heterogeneous-firm model of misallocation to study the effects of capital liberalization on aggregate productivity. In their framework two groups of firms face different costs of capital: only one group of firms can tap the capital market, while the other has to borrow funds from a monopolist bank. The two groups of firms also have different markups, which coincides with the (sector-specific) markup of the bank in one case, and is instead equal to unity for the group of firms that can borrow directly from households. Guided by their stylized framework Larrain and Stumpner (2017) are able to provide reduced-form evidence consistent with the idea that episodes of financial liberalization work their effects on aggregate productivity also through markups, which is consistent with one of our findings. However, in our framework we do not need specific financial shocks to derive our aggregate results: given our setup, the simple presence of financial frictions affects the pass-through effect of any economic shock (e.g. a demand shock) on prices and welfare.

In a related paper, Gopinath et al. (2017) introduce the idea of size-dependent borrowing constraints in a small open economy model with heterogeneous firms and capital adjustment costs. They show how a model with the presence of financial frictions depending on firm size is better able to replicate actual firm behavior in the data, with capital inflows going to firms that have higher net worth but are not necessarily more productive, thus leading to a potential misallocation. While in our paper we do not directly address the issue of resource misallocation, the structural measure of firm-level financial constraint we are able to retrieve is significantly correlated with size, as firms with larger assets or turnover display systematically lower constraints in our data.

The paper also speaks to a literature that has introduced credit constraints in models of firm heterogeneity and international trade.[5] Manova (2013) incorporates financial frictions in a CES framework of heterogeneous firms in which firms use tangible assets as collateral, as in our model, in order to obtain loans from a perfectly competitive banking sector and cover part of their export costs (vs. part of production costs in our case). In her framework, credit constraints affect both the extensive and intensive margin of exports but the pass-through of financial frictions on prices is complete, as markups are constant. Our model with variable markups allows instead for an incomplete pass-through effect. Egger and Seidel (2012) introduce credit constraints in models of heterogeneous firms with endogenous markups and the use of collateral proportional to a firm's production cost, thus in line with our setup. Differently from our approach, however, they do not take into account the heterogeneity of firms in access to external finance. As a result, financial frictions enter in their profit-maximizing quantities and prices through a cost cutoff parameter driven (among others) by a common collateral requirement, with no role for the heterogeneous cost of collateral for firms, which is a distinct feature of our model. Peters and Schnitzer (2015) incorporate financial frictions in a variable markup framework with endogenous technology adoption, in which the cost of purchasing the advanced technology has to be financed externally. However, as they assume that technology adoption results in an increase of the price margin by a fixed amount, they do not work out the implications of financial frictions for markups.

The rest of the paper is organized as follows. We present our theoretical framework in Section II. Section III describes our data and introduces our estimation routines for financial capability, productivity and markups. In Section IV we discuss the empirical strategy used to test our predictions, including our structural estimate of firm-level collateral requirements, and present our main results together with robustness checks. Section V concludes.

[5] We do not work out an open economy version of our model in this paper, as it would not change our main results.

2 Theoretical Framework

2.1 Setup and identification

We consider an economy with L consumers, each supplying one unit of labor. Consumers can allocate their income over two goods: a homogeneous good, supplied by perfectly competitive firms, and a differentiated good, produced under monopolistic competition. In order to produce, liquidity constrained firms need to finance a share of their production costs through loans from a perfectly competitive banking sector. To provide a loan, banks require firms to pledge an amount of tangible assets to be used as collateral. There are two types of tangible assets: redeployable (land, buildings) and non-redeployable (machinery). Redeployable assets are easier to collateralize. Firms have a positive initial endowment out of which they can purchase tangible assets to use as collateral, but are heterogeneous in financial capability: more financially capable firms have a lower cost of obtaining redeployable assets. Firms are also heterogeneous in marginal costs (productivity), and learn about their specific level of financial capability and productivity after having incurred a sunk entry cost. Once endowed with information on their financial capability and marginal costs, firms that can cover production costs and satisfy the liquidity constraint (net revenues at least equal to the repayment of the loan) stay in the market.

The two sources of heterogeneity, productivity and financial capability, are ex-ante uncorrelated as they are drawn from two independent probability distributions. Still, they jointly influence firm behavior: a firm with a higher level of financial capability will face lower costs for the required amount of collateral, which in turn influences her overall cost structure, and thus, given the specific firm-level productivity, her optimal production choice.

To disentangle the effects of financial capability from marginal costs and identify the model, we exploit an empirical regularity detected in our data and already discussed in the literature (Rampini and Viswanathan, 2013), i.e. the proportionality between firms' output and collateral. In equilibrium, more productive (lower cost) firms end up with higher output, whose financing requires a larger volume of loans, and thus a higher amount of collateral. Motivated by this empirical regularity, in our framework banks require a fixed amount of collateral per unit of output that varies across sectors.[6] We can then derive an expression for the cost advantage that a firm characterized by a given level of financial capability has in creating the required amount of collateral. Since the collateral requirement is exogenous to the firm, her cost advantage influences the firm's output, but is independent of marginal costs. The latter allows identification of the model.[7]

Importantly, the assumed orthogonality between firm-specific productivity and financial capability is verified in the data: our non-parametric measure of the firm-specific financial capability is uncorrelated with a standard proxy of firm-level productivity (value added per employee), as well as with our computed TFP measures (see Appendix D).

2.2 Demand and Production Technology

Consumers exhibit love for variety with horizontal product differentiation and quasi-linear preferences, and thus variable markups (e.g. as in Melitz and Ottaviano, 2008). Specifically the utility function is:

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

where the set Ω contains a continuum of differentiated varieties, each of which is 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.

[6]To the extent that output and assets are positively correlated, this is equivalent to the assumption that the share of productive assets that can be collateralized varies across sectors. We also introduce a firm-level collateral requirement, i.e. varying within sectors.

[7]Technically the model yields a profit equation with a separable cost advantage term related to the firm's financial capability.

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 the demand for the homogeneous good being positive, i.e. $q_0 > 0$, and solving the utility maximization problem of the individual consumer, it is possible to derive the inverse demand for each variety:

$$p_i = \alpha - \gamma q_i^c - \eta \int_{i\in\ \Omega} q_i^c \ di \ , \forall i \in \Omega \tag{2}$$

By inverting (2) we obtain the individual demand for variety i in the set of consumed varieties Ω^*, where the latter is a subset of Ω for which $q_i^c > 0$, and retrieve the following linear market demand system:

$$q_i = Lq_i^c = \frac{\alpha L}{\gamma + \eta N} - \frac{L}{\gamma} p_i + \frac{\eta N \overline{p} L}{\gamma(\gamma + \eta N)} \ , \forall i \in \Omega^* \tag{3}$$

In the above expression N represents the number of consumed varieties, which also corresponds 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. In order to obtain an expression for the maximum price that a consumer is willing to pay, we set $q_i = 0$ in the demand for variety i and obtain the following:

$$p_{max} = \frac{\alpha\gamma + \eta N \overline{p}}{\gamma + \eta N} \tag{4}$$

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

Conditional on having adequate financial resources, firms produce using labor, 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 goods are produced under constant returns to scale, but entry in the differentiated goods industry involves a sunk cost f_E. Firms are heterogeneous in productivity, having a firm-specific marginal cost of production $c \in [0, c_M]$ randomly drawn from a given distribution. In equilibrium the output level $q(c)$ of a firm with cost c will thus be equal to the total demand for its own variety.

2.3 Financing of firms

In our framework, liquidity constrained firms need to borrow money from banks in order to finance a fixed share $\rho \in [0, 1]$ of their production costs $cq(c)$. Banks, which operate in a perfectly competitive banking sector, define contract details for loans and, based on their participation constraint (see infra), can make a take-it or leave-it offer to firms specifying the collateral needed against the loan. 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.[8] Given production technology, firms characterized by a larger output $q(c)$ also have larger production costs $cq(c)$ whose financing requires a larger volume of loans. In order to disburse a loan banks require $\beta > 0$ units of collateral for each unit of output. The unit requirement β is chosen by the bank and varies across sectors (as e.g. in Manova, 2013): it is therefore exogenous from the perspective of individual firms. It then follows that a firm characterized by marginal costs c and total output $q(c)$ has to pledge an amount of collateral equal to $\beta q(c)$ to obtain the loan.[9]

The above setup is supported by empirical evidence. In our data, regressing a firm's (log) turnover on firm's bank liabilities yields a positive and significant coefficient, i.e. larger firms

[8]Expenditures on collateral and the sunk cost f_E are incorporated in the entry decision of the firm via the expected profit equation, and thus enter in the expression of the industry equilibrium.

[9]We do not need to impose ex-ante an upper bound to β, because collateral will enter into the firm's profit as a cost and thus, if the unit requirement β is too high with respect to the firm's optimal size, the firm would 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. Similar considerations apply when we model a firm-specific collateral requirement.

require more bank loans.[10] Moreover, the idea that banks require an amount of collateral that is proportional to a firm's output is an empirical regularity detected in the literature (Rampini and Viswanathan, 2013) and again confirmed in our data: regressing firms' bank liabilities on tangible assets, a proxy for collateral, also yields a positive and significant coefficient, supporting the existence of a proportional relation between output and the amount of collateral pledged.

Another key feature of our framework, also in line with empirical evidence, is the idea that firms differ in their access to finance. Similar to Irlacher and Unger (2016), we find a high dispersion of access to credit (proxied as tangible over total assets) across firms within narrowly defined (NACE-4 digit) industries in our dataset, also after controlling for firm-level characteristics (e.g. productivity). To encompass in the model the idea that different firms might have a more or less privileged access to external finance, we exploit the distinction made in the literature between redeployable assets (Re) constituted by land, plants and buildings, and non-redeployable assets (NRe), e.g. machinery and equipment (Campello and Giambona, 2012). Redeployable assets are easier to resell on organized markets: being more liquid, they can be more easily used as collateral and thus facilitate firms' borrowing. Non-redeployable assets are more firm-specific and with a value that deteriorates over time (e.g. due to technological obsolescence): as such, they are less easy to be used as collateral.[11]

We posit that firms use tangible assets as collateral (as e.g. in Manova, 2013), and that firms have a different ability in negotiating the price of the redeployable assets they acquire, with each firm having a specific level of financial capability $\tau \in [0, 1]$ randomly drawn from a probability distribution and independent of marginal costs $c \in [0, c_M]$. Firms with higher financial capability τ end up paying relatively less for their redeployable assets.

[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] More in general, under asset-based lending, collateralizable assets include inventory, accounts receivable, machinery and equipment, real estate or the cash flow. Note that it is always possible to express these assets, and thus collateral, as a generic function of a firm's output.

As redeployable assets are part of the tangible assets that are used as collateral, the function $C(\tau)$ then maps the marginal cost of collateral for the firm characterized by a level of financial capability τ, with $C(\tau)$ strictly decreasing in τ.[12] From here we can define the financial capability cutoff $\widetilde{\tau} < \tau$ such that $C(\widetilde{\tau}) = C_{max}$, that is a firm characterized by the (cutoff) financial capability $\widetilde{\tau}$ would obtain no advantage in the price of redeployable assets with respect to other firms, i.e. her marginal cost of collateral would be the upper bound value C_{max} of the cost function. It then follows that the function

$$\theta(\tau) = C(\widetilde{\tau}) - C(\tau) \tag{5}$$

is increasing in τ and describes the cost advantage in terms of raising collateral that a firm characterized by financial capability τ will have with respect to the cutoff firm. By definition, the financial capability cutoff firm $\widetilde{\tau}$ will have no cost advantage, i.e. $\theta(\widetilde{\tau}) = 0$.

Alternatively, one could look at the relationship lending literature, which studies how the relations of managers with banks increase funds availability and reduce loan rates.[13] In our framework firms would be more or less financially capable depending on their share τ of managers more skilled (or better connected) in bargaining with banks, and thus able to reduce the overall cost of collateral. In this case, the financial capability cutoff firm would have no managers with such relations ($\widetilde{\tau} = 0$), and thus, as before, no cost advantage, i.e. $\theta(\widetilde{\tau}) = 0$.[14]

The implications of heterogeneity in financial capability can be seen considering the

[12]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 $\partial C(\tau)/\partial\tau < 0$.

[13]The channels through which bank-managers relations can have an impact on a firm's 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). Elyasiani and Goldberg, 2004 provide a general review of this literature.

[14]In our model both asset redeployability and relationship lending can be considered as channels that can explain heterogeneity in access to finance by firms, as they both map the same parameter $\theta(\tau)$ that enters our equilibrium equations. However, 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 nominal asset value) in order to retrieve a measure of financial capability from our data.

case of all firms having the same financial capability $\bar{\tau}$. In this case firms in the industry would end up with the same marginal cost of collateral $C(\bar{\tau})$. As a result, productivity would remain the only firm-specific variable characterizing the industry equilibrium: a given level of marginal costs c would in fact determine the firm's size $q(c)$, the volume of the required loan as a share of total production costs and hence, via the collateral requirement β requested by banks, the total cost of collateral to pledge. In this case, financial frictions would play a role only through changes in collateral requirement, with a similar effect for every firm in the industry. Introducing heterogeneity also on financial capability τ, on top of productivity, allows instead to derive a more complex interaction between productivity and financial frictions in the industry equilibrium.

2.4 Bank and firm problem

Firms that fund a share $\rho > 0$ of their total production costs $cq(c)$ have to repay $R(c)$ to banks. Repayment occurs 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 $\beta q(c)$. To close the deal and make an offer to the firm, the participation constraint of a bank is:

$$-\rho cq(c) + \lambda R(c) + (1-\lambda)\beta q(c) \geq 0 \tag{6}$$

that is, the value of the disbursed loan $\rho cq(c)$ has to be equal to its expected reimbursement, either as a repayment $R(c)$ or through the seizing 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 a liquidity constraint is satisfied, such that net revenues are at least equal to the repayment of the loan $R(c)$ to the bank. Specifically, the liquidity constraint incorporates the two sources of firm heterogeneity in marginal costs and financial capability (c, τ) as follows:

$$p(c,\tau)q(c,\tau) - (1-\rho)cq(c,\tau) + \theta(\tau)q(c,\tau) \geq R(c,\tau) \tag{7}$$

that is, firm will apply for a loan if the difference between revenues and the internally financed fraction of the costs, net of the cost advantage that a firm with financial capability τ has in generating the required amount of collateral, is larger or equal then the repayment of the loan necessary for production.[15]

Each firm in the differentiated sector maximizes the following profit function

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

As there are two sources of heterogeneity (c and τ) and imperfect financial markets, in order to solve the firm's problem we have to consider the cutoff level of marginal production costs at which profits are zero (i.e. the free exit condition as in Melitz and Ottaviano, 2008) under, in turn, the bank's participation constraint (6), the demand for the supplied variety (3) and the liquidity constraint (7), conditional on the cost advantage in collateral (5).

From equation (6) it is possible to derive an expression for the repayment function:

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

Plugging the expression above in the profit function, and maximizing profits under the linear demand (3) yields the FOC:

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

[15] We have written the cost of the firm in raising collateral already with respect to the cost advantage $\theta(\tau)$, i.e. conditional on the financial capability cutoff $\widetilde{\tau}$. Clearly the latter has to be endogenized to close the model (see infra).

Rearranging the terms above, we obtain the supply curve:

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

We can now use the liquidity constraint (7) to derive an expression for the production cost cutoff c_D. Firms characterized by a level of marginal costs such that the associated 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 4). We can thus rewrite the liquidity constraint as follows:

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

Substituting and rearranging the terms in the equation above 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 constants.

Our results are still conditional on the financial capability cutoff $\widetilde{\tau}$ with respect to which the cost advantage is calculated. In order to endogenize $\widetilde{\tau}$ in the expression of p_{max}, recall from expression (5) that $\theta(\tau)$ is increasing in τ. Hence, the maximum price charged by a firm in our setting is the one set by the least financially capable 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 then 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. 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 of p_{max} in (4) and (9), substituting it in the above equation and rearranging, we obtain the equilibrium price charged by a (c,τ) firm

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

From here, by subtracting the marginal cost we derive the expression of the equilibrium markup of a (c,τ) firm:

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

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), as well as the heterogeneity of firms in financial capability, i.e. the term $\theta(\tau)$, both affect the expression of the markup, as summarized in the following

Proposition #1. *The equilibrium markup $\mu(c,\tau)$ of a firm characterized by a pair (c,τ), and a given level of collateral requirement β, is ceteris paribus an increasing function of its cost advantage $\theta(\tau)$ in raising collateral.*

In other words, similar to productivity, more financially capable firms do not transfer all the cost advantage they have in generating the required amount of collateral into lower prices, but rather retain relatively higher margins. Moreover, the markup is also affected by the collateral requirement β, as the latter enters in the expression of the parameter ϕ, the cutoff c_D and, in principle, the same cost advantage $\theta(\tau)$ (see for example the formalization proposed in Appendix A). To understand how a change in collateral requirement affects firm behavior in our model, we need to solve for the industry equilibrium.

2.5 Industry equilibrium and economic shocks

In order to characterize the industry equilibrium, we have to solve for the value of the cutoffs c_D and $\widetilde{\tau}$. As we have no ex-ante prior on the distribution of financial capability of firms, 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 still uniform with density equal to $f(\tau) = \frac{1}{1-a}$.[16]

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 functions 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 functions 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

[16]The assumption of a uniform distribution of τ implies that the financial capability cutoff $\widetilde{\tau}$ does not vary with market characteristics, whereas the cost cutoff c_D of the industry is a function of the distribution of surviving firms' productivity. This simplification allows to introduce a second source of heterogeneity in the firm-level equilibrium equations, while maintaining the model tractable at the level of industry aggregates. In any case it can be shown that, independently on the distributional assumption, a relevant shock (e.g. a change in market size) affects in the same way both the financial capability and the production cost cutoffs, and thus the industry equilibrium.

in equilibrium:

$$\pi(c,\tau) = \frac{L}{4\gamma}\left[\omega c_D - c - \phi + \theta(\tau)\right]^2 \tag{12}$$

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

$$\pi^e(c,\tau) = \int_0^{c_D}\int_a^1 \frac{L}{4\gamma}\left[\omega c_D - c - \phi + \theta(\tau)\right]^2 \; dF(\tau)\; dG(c) = f_E \tag{13}$$

Since $dG(c) = g(c)dc$ and $dF(\tau) = f(\tau)d\tau$, we can rewrite the integral as:

$$\pi^e(c,\tau) = \frac{Lk}{4\gamma c_M^k}\int_0^{c_D}\int_a^1 \left[\omega c_D - c - \phi + \theta(\tau)\right]^2 c^{k-1}\; d\tau\; dc = f_E \tag{14}$$

As shown in Appendix B, one can prove that a positive solution always exists for c_D and it is unique conditional on a choice of c_M. Average prices and markups are a function of the average marginal cost c and financial capability. Following Melitz and Ottaviano (2008), we define average marginal costs as:

$$\overline{c} = \frac{\int_0^{c_D} cg(c)dc}{G(c_D)} = \frac{kc_D}{k+1} \tag{15}$$

Similarly we can derive an expression for the average markup charged by firms active in the market, 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:

$$\overline{\mu} = \frac{1}{2}\left[\frac{\omega k + \omega - k}{k+1}c_D - \beta\psi\right] \tag{16}$$

with $\psi > 0$ being a constant depending on the parameters a, δ and λ of the model.

In order to analyze the effects of an economic shock on average markups, we can consider the effects of a change in the market size parameter L. Differentiating equation (16) yields

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

As shown in Appendix C, we have that $\partial c_D/\partial L < 0$, and thus $\partial \overline{\mu}/\partial L < 0$, i.e. 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.[17]

Financial frictions, however, play a role in the reaction of the economy to the shock, as the magnitude of the derivative of the cost cutoff with respect to L depends, among others, on the amount of collateral requirements 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 discussion). We can thus state that:

Proposition #2. *An increase in market size induces pro-competitive effects on the average industry markup. Financial frictions in the form of higher collateral requirements mitigate these effects.*

3 Data and estimation of covariates

3.1 Firm-level data

Our firm-level data derive from the survey on European Firms in a Global Economy (Efige), a research project funded by the European Community's Seventh Framework Programme

[17] Given the uniform distributional assumption on τ, in this setting financial capability does not affect the reaction of average markups to a change in market size. Extending the model to the case of an endogenous financial capability cutoff, i.e. solving the free entry condition also for $\widetilde{\tau}$, would in any case yield a similar pro-competitive effect on average markups.

(FP7/2007-2013).[18] The dataset collects around 150 variables for a representative sample of some 15,000 manufacturing firms in the following countries: Austria, France, Germany, Hungary, Italy, Spain, and the United Kingdom, as reported in in Table 1.

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 firm-level information present in the Efige dataset has been matched with balance sheet data drawn from the Amadeus database managed by Bureau van Dijck, and collected from 2002 to 2013.

3.2 Estimation of financial capability

Guided by our theoretical model, and using simple balance sheet information, it is possible to retrieve an estimate of the cost advantage $\theta(\tau)$ accruing to each firm. As firms are able to collect collateral at different costs, and collateral is constituted by tangible assets, it then follows that the nominal value of a firm's tangible assets (TA) observed in a firm's balance sheet should be decreasing in the firm's financial capability τ, once controlling for firm size and industry (technology) effects. The intuition here is that all firms within the

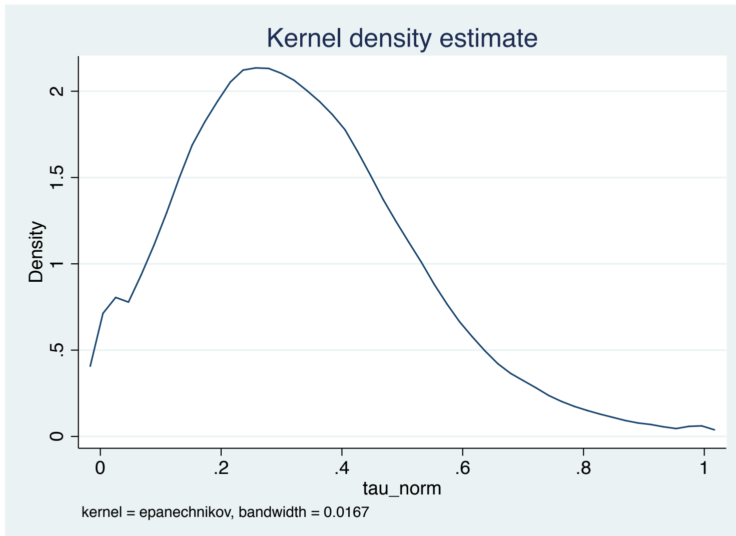
[18]The complete questionnaire is available on the Efige web page, www.efige.org. The sampling design follows a stratification by industry, region and firm size. Firms with less than 10 employees have been excluded from the survey, that instead presents an oversampling of firms with more than 250 employees to allow for adequate statistical inference for this size class. Descriptive statistics are reported in Appendix D. 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 are available in Altomonte and Aquilante (2012).

same industry would be required to collect approximately the same amount β of TA per unit of output to use as collateral: firms with higher τ will obtain that required amount at a lower cost, and thus, controlling for size, would display a lower book value of tangible assets in their balance sheets. Also, for the same reason, the cutoff firm $\tilde{\tau}$ would have the highest nominal value of tangible assets across firms of that specific size and industry. From here we can estimate $\theta(\tau)$ in three stages. First, we create bins of firms characterized by the same size within each industry (deciles of turnover, with quintiles and twentiles used as robustness). Second, for each bin within each industry, we identify the upper bound level of nominal tangible assets recorded by firms, calculated as the average value of the top 5% largest TA (robustness with 1%): this value represents the tangible assets of the cutoff firm(s). Finally, we compute the firm-specific cost advantage $\theta(\tau)$ by taking the ratio between the value of tangible assets of the cutoff firm and the TA value of specific firms, within each size/industry partition. We retrieve from here an index that we normalize between 0 (cutoff firms) and 1 (maximum financial capability).

Figure 1 reports the distribution of the retrieved measure of financial capability across firms in our sample, which gives us a good proxy of the heterogeneity with which different firms face different costs in their access to finance. Considering all combinations of firms' size ranges (quintiles, deciles, twentiles) within industries, different cutoff levels of tangible assets (1%, 5%), as well as different industry aggregations (at the 2 or 3-digit level), we can obtain several versions of our firm-specific cost advantage measure, which we will use as sensitivity checks in testing our Propositions.

Importantly for our identification strategy, all the correlations between our retrieved measure of firm-level financial capability and productivity are not larger than 0.06, as shown in the first column of Table D.2 in Appendix D.

Figure 1: Distribution of $\theta(\tau)$



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 ratios of each firm's TA value with respect to the cutoff firm's TA, within every size/industry partition, and then bounding the index between zero (cutoff firms) and one (maximum financial capability).

3.3 Estimation of productivity and markups

In order to estimate markups and productivity at the firm level we start from De Loecker and Warzynski (2012, henceforth DLW), who estimate markups combining the output elasticity on a input with the share of the same input's expenditure on total sales. The DLW methodology is particularly suited for our estimation strategy for two reasons. First, it obtains output elasticity from the estimation of a general production function, allowing for flexible technologies and different sources of firm heterogeneity. Second, the correlation between the estimated markups and firm-level characteristics is not affected by the availability of real vs. nominal output (revenue) data.[19] The latter allows us to test our Propositions using simple

[19] De Loecker and Warzynski (2012) discuss how, under a Cobb-Douglas technology, the output elasticity reduces to a constant, and thus the bias induced by unobserved output prices impacts only the estimate

balance sheet information at the firm-level.

Additional problems nevertheless arise when estimating our model in a setting in which financial capability is heterogeneous across firms. The reason is twofold. On the one hand, our proxy of financial capability $\theta(\tau)$ is likely to be correlated to the (unobserved) firm-specific price of capital. If the latter is unaccounted for, this input price variation typically leads to a downward bias in the estimated coefficients of the production function from which markups are calculated, an issue discussed in detail by De Loecker and Goldberg (2014). Moreover, the same idiosyncratic variation in the price of capital would remain in the error term of the production function, thus ending up in our TFP estimates. This induces a potential problem of multicollinearity between TFP and financial capability when structurally estimating Equation (11). For these reasons, we have modified the standard algorithms through which TFP is estimated.

Technically, we have estimated our production function coefficients relying on Wooldridge (2009), which proposes to improve on the Ackerberg, Caves and Frazer (2015, henceforth ACF) algorithm originally employed in De Loecker and Warzynski (2012) through the use of a GMM framework. In our baseline measure, we have computed estimates of the production function following Woolridge (2009), both through the standard algorithm and augmenting the set of regressors with our proxy for financial capability.[20] As a robustness check, we have also estimated the production function through the ACF approach, both correcting the control function with financial capability and in its standard version, thus replicating the original DLW methodology. The correlation at the firm level between all these different measures of productivity and the retrieved measure of financial capability is always very small (see Table D.2 in Appendix D), thus confirming in the data the substantial orthogonality of these two variables.

level of the markup, not its correlation with firm characteristics.

[20]When not controlling for the firm specific financial capability, our estimates show an upward bias in the estimated productivity, i.e. a downward bias in the estimated coefficients of the production function, in line with the effects postulated by De Loecker and Goldberg (2014).

We have then used the estimated production function coefficients in order to compute different measures of firm-level markups. Specifically, Table 2 reports the median values and standard deviations of four different firm-level markups. The first two measures are markups estimated through the Woolridge (2009) algorithm, both in the standard and corrected version discussed above. The third measure of markups is computed using production function coefficients estimated through the standard ACF routine, as in De Loecker and Warzynski (2012). The fourth estimate reports markups estimated via the ACF algorithm in which the control function has been corrected for financial capability. We will employ these different measures to provide additional robustness checks in the tests of our Propositions.

Table 2: Markup estimates: median values and standard deviations

Estimation method	Median	Standard deviation
Wooldridge (no correction)	1.2063	0.7543
Wooldridge (correction)	1.2152	0.7066
ACF (no correction)	1.0668	0.4016
ACF (correction)	1.0886	0.6267

4 Empirical analysis

4.1 Financial capability, productivity and markups

We structurally estimate the markup equation (11)

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

at the firm-year level, with the dependent variable $\mu(c,\tau)$ being the markup estimated through DLW (2012), as previously discussed. In terms of covariates, ωc_D and ϕ are fixed effects or controls (depending on specification), c is (the inverse of) our retrieved TFP measure at the firm-level, while $\theta(\tau)$ is the cost advantage term stemming from the heterogeneous financial capability of firms, retrieved as described in section 3.2. We test our markup equation for the years 2002-2013 under various specifications plus a number of sensitivity and robustness checks. In addition, as heterogeneity in financial capability is relevant only for liquidity constrained firms, we always condition our estimates on firms that have requested a loan from a bank.[21]

Table 3 presents our benchmark results, in which our proxy $\theta(\tau)$ for financial capability is estimated by deciles of sales, and the cutoff level of tangible assets is calculated on the top 5% of the distribution for each size decile within each NACE-2 digits and year. Productivity and markups are estimated through the Woolridge (2009) algorithm, corrected for financial capability. In column (1), we employ a full set of firm fixed effects to wipe out any unobserved heterogeneity at the firm level that can drive the results, as well as year fixed effects. Results confirm that markups are positively and significantly correlated with productivity and that, even controlling for productivity, more financially capable firms display significantly higher markups as predicted by the theoretical framework. In column (2) we control for the possibility that some financial/price shock happening over time across some firms (and thus not picked up by our firm FE) might drive the results, introducing as an additional control a country-time change in collateral requirement as retrieved from the ECB Bank Lending Survey.[22] While the latter is negative and significant, in line with the idea that higher average collateral requirements increase costs and thus reduce the markup of firms, our main results are confirmed.

Insofar we have identified the effects of productivity and financial capability through the within variation in the data, thus implying that firms can adjust their allocation of tangible assets, productivity and, consequently, markups over time. If our theory is valid, however, our results should also hold when we identify the effects through the between variation in

[21] A total of 14,139 firms in our data, i.e. 96% of the sample, have requested a bank loan.

[22] 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 have not been all similar across countries.

the data, i.e. across firms.

Table 3: Test of Proposition 1

	(1) Within estimator	(2) Within estimator	(3) Between estimator	(4) OLS
	decile of sales, top 5% TA cutoff	decile of sales, top 5% TA cutoff	decile of sales, top 5% TA cutoff	decile of sales, top 5% TA cutoff
	all years	all years	all years	only 2008
Dependent variable	$\ln(\mu)_i$	$\ln(\mu)_i$	$\ln(\mu)_i$	$\ln(\mu)_i$
$\ln(\text{TFP})_i$	1.547***	1.594***	1.363***	1.462***
	(0.0109)	(0.0139)	(0.0123)	(0.0191)
Financial capability$_i$	0.437***	0.484***	0.205***	0.280***
	(0.0189)	(0.0231)	(0.0237)	(0.0375)
Change in collateral requirement		-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
Robust SE	YES	YES	NO	YES

***,**,* = indicate significance at the 1, 5, and 10% level, respectively. The dependent variable is the (log of) markups estimated as in De Loecker and Warzynski (2012), using production function coefficients estimated as in Wooldridge (2009). The financial capability variable is computed across deciles of sales, with firms having the top 5% of TA considered as the cutoff firms. TFP is computed through a modified version of Wooldridge (2009), cleaning production function estimates for firm-level financial capability. Change in collateral requirements indicates the percentage increase/decrease in the collateral requirements by banks. All specifications estimated with robust standard errors.

In columns (3) and (4) we thus replicate our analysis reported in column (2) without firm fixed effects. We include a set of country×industry fixed effects to capture all possible spurious compositional effects beyond variation at the firm level. We also control for additional firms' characteristics that might be correlated with both productivity and financial capability, notably the (logarithm of) firm's age as well as firm size (employment), variables that are known to exert an impact on on TFP and financial constraints (see for example

Hadlock and Pierce, 2010).[23] Specifically, in column (3) we keep the panel dimension through a between estimator, while in column (4) we focus on the cross-section for the year 2008. In both cases the coefficient of financial capability decreases by around a third with respect to the within-estimation, but remains positive and highly significant.

In Table (4) we proceed with some sensitivity and robustness checks, reporting the results of the estimated coefficients of the two key variables of our model, productivity and financial capability, in different specifications of the markup regression, while always controlling for firm fixed effects (unless differently specified). In a first battery of tests (1 to 5), we change the estimation procedure of $\theta(\tau)$. Namely, in row (1) we estimate the latter by shrinking the size ranges of firms' sales to quintiles, and widening the cutoff level threshold of tangible assets to the top 10% of firms in each NACE-2 digit industry and year. In row (2) we do the opposite, broadening the size ranges of firms within which we estimate $\theta(\tau)$ to twentiles, and narrowing the cutoff level of tangible assets to the top 1% of the distribution in each industry-year. In rows from (3) to (5) we replicate the three different estimation methods of our benchmark Table 3 (FE, BE and OLS on the 2008 cross-section) with financial capability now measured within each NACE-3 digits industry and year, i.e. for a total of around 100 industries. The sign and significance of our key parameters is always confirmed, with little changes in magnitude with respect to our benchmark results.

In a second group of sensitivity checks (rows 6 to 8), we revert to our benchmark measures of financial capability and TFP used in Table 3, but we experiment with the methods through which markups have been estimated. This, in order to avoid picking up some spurious correlation deriving from the markup estimation method itself. In row (6) we employ markups retrieved from production function coefficients estimated with the ACF (2015) method and

[23]Industry fixed-effects are retrieved from Manova (2013) as measures of financial vulnerability (i.e. the extent to which a firm relies on outside capital for its investment). Firm size is controlled as a categorical variable, varying from 1 to 4 based on the firm having between 10-19, 20-49, 50-249 or more than 250 employees, respectively. The choice of a categorical variable is driven by the willingness of reducing 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 to the size categories.

corrected for financial capability; in row (7) we replicate the results with markups estimated from production function coefficients calculated through the standard Woolridge (2009) algorithm, i.e. not corrected for financial capability; in row (8) we repeat the exercise using standard ACF (2015) estimates, thus replicating the original De Loecker and Warzynski (2012) measure of markups. Once again the sign and significance of our key parameters of TFP and financial capability are confirmed.

Table 4: Test of Proposition 1 - Sensitivity

	TFP		Financial Capability			
	Coeff	Std. Err.	Coeff	Std. Err.	Obs.	R2
Baseline	1.594***	(0.0139)	0.484***	(0.0231)	35,525	0.836
Different measures of Financial Capability						
(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
Alternative estimates of Markups						
(6) Markups ACF (corrected)	0.707***	(0.00922)	0.458***	(0.0201)	40,034	0.645
(7) Markups Wooldridge (not corrected)	1.575***	(0.0137)	1.283***	(0.0260)	35,565	0.825
(8) Markups ACF (not corrected)	1.585***	(0.0129)	0.655***	(0.0231)	39,777	0.836
Omitted variables (Cross Section)						
(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

***,**,* = indicate significance at the 1, 5, and 10% level, respectively. The model specification follows column (2) of Table 3 (column (4) for the cross-section). All estimates with robust standard errors.

Finally, rows (9) to (12) of Table 4 present a number of robustness checks on the cross-section specification. The purpose is to assess whether our specification remains significant also when controlling for additional firm-level variables potentially correlated with both financial capability and markups. To that extent, we use three questions available in the Efige survey for the year 2008. A first question looks at the number of banks used by the firm. The question is answered by almost the entire sample and shows an average of three banks per firm (two for the median firm). The intuition is that a firm better connected to a relatively high number of banks might have access to financial conditions that entail both a lower cost of collateral, and thus a higher $\theta(\tau)$, and the possibility to charge relatively higher markups (as losses would be covered by an extension of the credit lines). In this case, the relation between financial capability and markups might be spuriously driven by this omitted variable. The second question we use relates to the R&D investments incurred by the firm. The idea is that a firm could exploit its higher financial cost advantage to invest in R&D and innovation, thus increasing either her physical productivity or the quality of her products. Both elements end up into a higher revenue TFP and higher markups, again generating a spurious correlation with financial capability. The third characteristic that we observe in the data and we control for in our cross-sectional estimates is whether a firm has been consistently exporting over time part of its production. De Loecker and Warzynski (2012) in fact show that markups differ dramatically between exporters and non-exporters, being statistically higher for exporting firms; at the same time, exporting firms might be better able to raise collateral at cheaper costs. We control for each of these three characteristics in rows (9) to (11), respectively, while in row (12) we run our benchmark specification considering banks, R&D and export status together. All our main results remain unchanged.

4.2 Firm-level collateral requirements and average markups

Our second theoretical result states that financial frictions in the form of higher collateral requirements can mitigate the pro-competitive effects (lower average markups) generally induced by a positive economic shock such as, e.g., a larger market size. In order to test for this result and identify the average effect of financial frictions on markups, we need to exploit variation across firms both in markups and in collateral requirements. The latter requires deriving firm specific collateral requirements from the model.

To that extent, we incorporate in our model and thus in the firm-level markup equation

(11) an additional source of heterogeneity related to a firm-specific collateral requirement β_i

$$\mu(c, \tau, \beta) = \frac{1}{2}\left[\omega c_D - c - \phi(\beta) + \theta(\tau, \beta)\right] \tag{17}$$

We can again estimate the equation in its structural form, with ωc_D and ϕ being fixed effects, c is (the inverse of) our retrieved TFP measure at the firm-level, while $\theta(\tau, \beta)$ is the cost advantage term stemming from the heterogeneous financial capability of firms, now embedding a firm-specific collateral requirement. As the latter is not observable, we estimate this equation separately for each industry including firm and time fixed effects, and use our original measure $\theta(\tau)$ as a proxy of firm-level financial capability. Then, the residuals of the regression can be interpreted as the deviation of the firm-year specific markup from the firm and year average markup within each industry, controlling for the firm-specific productivity and financial capability. We posit that this deviation is likely induced by the existence of firm-specific collateral requirements.[24] Technically, our proxy for β_i is thus constructed as the normalized residuals of the estimation of equation (17). In Appendix D we show the low level of correlation of our proxy with other regressors of the model, notably financial capability and TFP.

We perform two plausibility checks of this new proxy of firm-specific credit constraint. First, we regress the retrieved β_i on different proxies of a firm's net worth (total assets, tangible assets, operating revenue), controlling form firm and year fixed effects. The latter yields negative and significant coefficients, in line with the assumption of Gopinath et al. (2017) of size-dependent credit constraints. Second, in Appendix E we perform a detailed test our retrieved firm-specific collateral requirements against other standard measures of credit constraints at the firm-level existing in the literature (e.g. the Whited and Wu index),

[24]In other words, equation (17) correctly estimated using the (unobservable) term $\theta(\tau, \beta)$ should yield i.i.d. residuals. As we estimate it using $\theta(\tau)$, that is a proxy of firm-level financial capability derived considering an industry, rather than firm-specific amount of collateral per unit of output, the residuals of this estimation should incorporate a proxy of the firm-level collateral requirements β_i.

with consistent results.

Once endowed with a plausible measure of β_i, we can test the model around an economic shock that significantly changes the market size L of an industry. To that extent, we exploit the sudden, ample and symmetric collapse of export flows incurred by European countries during the credit crisis of 2008/09 (Baldwin, 2009). We start from BACI trade data at the country-industry-year level, and create a dummy variable $T_{zjt} = 1$ if the yearly growth of a given zj export flow in each country-industry pair in year t is in the bottom 25% of the overall growth rate distribution of export flows.

Our theoretical model predicts that $\partial\overline{\mu}/\partial L < 0$, i.e. an increase in market size tends to reduce the average industry markup, in line with the pro-competitive effects identified in the literature. As a result, in our empirical setting, we should obtain a positive sign of the economic shock dummy in the augmented markup equation, as lower exports (smaller market size) lead to higher markups. Our theoretical setting also points at a negative sign of the firm-specific collateral requirement: with higher collateral requirements some firms would not be able to satisfy the liquidity constraint, as the repayment function $R(c)$ becomes larger. Hence, the least efficient firms in the market (in terms of production) would exit, generating a fall in the production cost cutoff c_D, and thus a reduction of markups. Finally, we should also observe a negative sign of the interaction between the economic shock and the collateral requirement, as Proposition 2 states that, on average across firms, the effect of the economic shock should be smaller the higher is the collateral requirement.

Table 5 reports the results of our estimation for the time window 2006-2009, i.e. around the economic shock of the end of 2008.[25] Since we are testing for an effect on the average industry markup across firms, the model is estimated as a pooled OLS. We add controls for the evolution of credit markets in a given country×year (share of bank credit/GDP and amount of non-performing loans in the bank sector/GDP, as retrieved from Eurostat), industry and year fixed effects, as well as individual time-varying firms' characteristics (age

[25] We obtain similar results with the time window 2007-2010.

and size). Moreover we always employ bootstrapped standard errors, as we use an estimated proxy for firm-specific collateral requirements.

Table 5: Test of Proposition 2

	(1)	(2)	(3)	(4)	(5)
	decile of sales, top 5% TA cutoff	decile of sales, top 5% TA cutoff, Nace 3 digits	quintile of sales, top 10% TA cutoff	decile of sales, top 5% TA cutoff	decile of sales, top 5% TA cutoff
	Firm-specific CR	Firm-specific CR	Firm-specific CR	Firm-specific CR	CR above/below median
Dependent variable	ln(μ)i Wooldridge (correction)	ln(μ)i Wooldridge (correction)	ln(μ)i Wooldridge (correction)	ln(μ)i ACF (correction)	ln(μ)i Wooldridge (correction)
ln(TFP)i	1.362***	1.360***	1.361***	1.205***	1.366***
	(0.0137)	(0.0138)	(0.0132)	(0.0176)	(0.0132)
Financial capabilityi	0.222***	0.188***	0.209***	0.204***	0.224***
	(0.0278)	(0.0229)	(0.0252)	(0.0300)	(0.0287)
Collateral requirement (CR)i	-0.585***	-0.593***	-0.585***	-0.338***	-0.143***
	(0.0467)	(0.0503)	(0.0477)	(0.0552)	(0.0113)
Negative trade shock (NTS)	0.422***	0.415***	0.421***	0.518***	0.408***
	(0.0793)	(0.0870)	(0.0858)	(0.0897)	(0.0741)
CR*NTS	-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

***,**,* = indicate significance at the 1, 5, and 10% level, respectively. The dependent variable is the log of markups estimated as in De Loecker and Warzynski (2012). Financial capability is computed by decile of sales, assuming firms having the top 5% of TA to be the cutoff firms in columns 1, 2, 3, 5, and 10% in column 4. TFP is computed through a modified version of Wooldridge (2009), cleaning production function estimates for firm-level financial capability in columns 1, 2, 3, 5, and a modified version of Ackerberg, Caves and Frazer (2015) in columns 4. The negative economic shock is a dummy=1 if the yearly growth of a given export flow in a country*industry*year is in the bottom 25% of the overall growth rate distribution of exports. Collateral requirement is the variable β_i estimated from equation (17). All specifications are estimated with bootstrapped standard errors (1,000 reps).

In column (1), markups, TFP and financial capability are defined as in our benchmark specification. Results are in line with our prediction: on top of the standard sign and significance of TFP and financial capability, a negative economic shock leads to significantly higher markups, while tighter firm-specific collateral requirements lower them. Most importantly, the interaction between the economic shock and the collateral requirement is negative and significant, in line with Proposition 2. In columns (2) to (5) we provide a number of robustness checks of this result. In column (2) we use the measure of financial capability estimated at the NACE-3 digits level. In column (3) financial capability is retrieved by shrinking the size ranges of firms' sales to quintiles, and widening the cutoff level threshold of tangible assets to the top 10% of firms in each NACE-2 digit industry and year. In column (4), we employ as dependent variable markups estimated through the ACF (2015) algorithm. Finally, in column (5) we use as a measure of firm-level collateral requirement a dummy taking value 1 if a firm is above the median estimated β_i. All our results remain consistent with our theoretical priors.

5 Conclusions

In this paper we have introduced financial frictions in a framework of monopolistically competitive firms with endogenous markups and heterogeneous productivity. Before producing, firms need to obtain a loan necessary to cover part of production costs, for which they have to pledge collateral in the form of tangible fixed assets. In addition to productivity, firms are also heterogeneous in their financial capability: some firms have access to collateral at lower costs. As a result, both financial capability and collateral requirements enter together with productivity in the expression of the equilibrium firm-level markup.

Looking in particular at firm-level markups we find that, for a given level of collateral requirement, more financially capable firms do not transfer all the cost advantage they have in generating the required amount of collateral into lower prices, but rather retain relatively higher margins. The latter is an interesting finding, as it might explain part of the variation of firm-level markups across a given level of productivity typically observed in the data. Moreover we also find that at the aggregate level the presence of financial frictions can affect the pass-through effects taking place in episodes of economic liberalization, with important consequences in terms of welfare

Our theoretical results are validated exploiting a representative sample of manufacturing firms surveyed across a subset of European countries during the financial crisis. Guided by theory, we estimate for each firm financial capability, TFP and markups. We then employ those estimates to structurally retrieve from the model a firm-specific measure of collateral requirements useful to test our main propositions.

The latter measure can be obtained from simple balance sheet figures, and performs in line with other standard proxies of firm-level financial constraints existing in the literature. In future research, we plan to extend its application to different instances in which financial frictions are likely to affect firm-level outcomes, in particular in terms of reallocation of economic activities.

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A Heterogeneous access to finance

We provide here a possible micro-foundation of the generic function $C(\tau)$ denoting the marginal cost of collateral for a firm with financial capability τ. In order to produce, firms combine redeployable and non-redeployable 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 and elasticity of substitution between Re and NRe assets. These are exogenous parameters fixed by the industry-specific technology in which the firms operate, capturing the idea that certain industries require the use of relatively more redeployable assets (e.g. land) vs. others, or allow for different substitutability between redeployable and non-redeployable assets for production. As firms are required by banks to pledge β units of tangible assets per unit of output, the technological constraint for a firm willing to produce is

$$\left(\delta Re^{\frac{\sigma-1}{\sigma}} + (1-\delta)NRe^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} = \beta \tag{18}$$

A firm having a specific level of financial capability $\tau \in [0,1]$ is able to lower the requirement of redeployable assets by $1-\epsilon(\tau)$ units, with $\epsilon(\tau) \geq 0$ and strictly increasing in τ.[26] Given the technological constraint, the expenditure function computed in the optimal amount of redeployable and non-redeployable assets for a firm with financial capability τ and a β unit requirement for collateral then is

$$C(\tau) = \frac{\beta\,(1-\epsilon(\tau))}{\left[\delta^{\sigma} + (1-\delta)^{\sigma}\,(1-\epsilon(\tau))^{\sigma-1}\right]^{\frac{1}{\sigma-1}}} \tag{19}$$

in which $C(\tau)$ is strictly decreasing in τ. From Equation (19) it is possible to define the financial capability cutoff $\widetilde{\tau}$ such that $\epsilon(\widetilde{\tau}) = 0$: a firm characterized by the (cutoff) financial capability $\widetilde{\tau}$ would not obtain any type of advantage in the price of redeployable assets. The

[26] Guner et al. (2008) find that the financial expertise of directors plays a positive role in the investment policies adopted by the firm. Glode et al. (2012) model financial expertise as the ability in estimating the value of securities, showing how this characteristic increases the ability of firms of raising capital.

latter represents the upper bound in the marginal cost of collateral and is equal to:

$$C(\widetilde{\tau}) = \beta\left[\delta^{\sigma} + (1-\delta)^{\sigma}\right]^{-\frac{1}{\sigma-1}} \tag{20}$$

By subtracting (19) from (20) we get:

$$\theta(\tau) = C(\widetilde{\tau}) - C(\tau) = \beta[\nu(1-\eta(\tau))] \tag{21}$$

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 terms. Given the exogenous parameters, Equation (21) is increasing in τ and describes the cost advantage in terms of raising collateral that a firm characterized by financial capability τ will have with respect to the cutoff firm. As it can be easily seen, the financial capability cutoff firm characterized by $\epsilon(\widetilde{\tau}) = 0$ will have no cost advantage, i.e. $\theta(\widetilde{\tau}) = 0$.

B Existence and uniqueness of cost cutoff

Equation (14) sets the expected profits of a firm facing the choice of entering the market as:

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

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 being 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:

$$f(c_D) = \pi^e - f_E = A c_D^{k+2} + B c_D^{k+1} + C c_D^k - \frac{4 f_E \gamma c_M^k}{Lk}$$

By Rolle's Theorem, between two solutions of $f(c_D) = 0$ there is always a solution of $f'(c_D) = 0$. Hence if we can prove that $f'(c_D) = 0$ exists, then at least two positive values of the cost cutoff exist, as $c \in [0, c_M]$. Moreover, as long as the second positive cost cutoff is $> c_M$, the latter 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 Cartesio's Rule, $f'(c_D) = 0$ has at least two positive solutions, i.e. there is a solution to $f(c_D) = 0$.

C Derivative of cost cutoff with respect to L

Differentiating equation (16) yields

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

By 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 having been 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:

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

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

D Descriptive statistics

Table D.1 reports descriptive statistics for the year 2008, i.e. the year referred to in the questions related to financial capability and investment in R&D. Table C.2 reports instead the correlations among our retrieved right-hand side variables, namely financial capability $\theta(\tau)$, total factor productivity (estimated with the Wooldridge, 2009 algorithm), both in the standard format and including a correction for financial capability, our firm-level proxy of credit constraints β_i, as well as labor productivity (value added per employee) as robustness.

Table D.1: Descriptive statistics

	Obs.	Mean	Std. Dev.	Min	Max
Tangible Fixed Assets (2008)	12035	1903	4582.88	1,002	50204
Sales (2008)	10554	10986	24694.42	194	250214
Employees (2008)	9583	66	113.94	10	1062
Number of Banks	14571	2.99	2.02	1	14
Investments in R&D	14759	59.90%	0.49	0	1

Table D.2: Correlations of right-hand side variables

	Cost advantage $\theta(\tau)$	TFP Wooldridge not corrected	TFP Wooldridge corrected	Firm-level collateral requirement β_i	Value added per employee	Total asset
Cost advantage $\theta(\tau)$	1					
TFP Wooldridge not corrected	0.0316	1				
TFP Wooldridge corrected	-0.0651	0.4674	1			
Firm-level collateral requirement β_i	-0.0086	-0.0001	0.013	1		
Value added per employee	0.0307	0.3215	0.265	-0.0464	1	
Total asset	-0.2342	0.1099	0.1488	-0.0191	0.2871	1

E Firm-level collateral requirement

In this section we offer a plausibility check for our firm-level measure of collateral requirement. Since the literature has not reached an agreement on this topic yet (Farre-Mensa and Ljungqvist, 2016), we correlate our measure to a well-known proxy of firm-level financial constraints as derived from balance sheet data existing in the literature.

Table E.1: Replication of Whited and Wu (2006) with β_i

Dependent variable	Firm-level collateral requirement
Cash flow / Total assets	-0.329***
	(0.0196)
Payment of dividends	-0.0194***
	(0.00286)
Long term debt / Total assets	-0.0139
	(0.0135)
ln(Total assets)	-0.122***
	(0.00600)
Industry sales growth	0.0900***
	(0.0205)
Firm sales growth	-0.0841***
	(0.00491)
Obs.	45,256
R2	0.094
Number of marks	6,971
Firm FE	YES
Year FE	YES
Robust SE	YES

Note: The specification of the original Whited and Wu (2006) index is reported below:

$$WW = -.091CF/TA - .062DivPos + .021LTD/TA - .044ln(TA) + .102ISG - .035SG$$

where CF is Cash Flow/Total Assets, DivPos=1 if paid cash dividends, LTD/TA is long term Debt/Total Assets, TA is Total Assets, ISG is the industry sales growth while SG is a firms sales growth.

Specifically, we use a firm-specific index of financial constraints developed by Whited and

Wu (2006) and comprising information on firm-level cash-flow, dividends, long-term debt, firm sales and industry sales and their growth and total assets. The original index was estimated with a GMM estimation using firm-level data from quarterly COMPUSTAT data over the period 1975 to 2001. The higher the index, the more difficult (or costly) is for a firm to obtain external financing, thus in line with the interpretation of our β_i. Table E.1 above runs the same specification of Whited and Wu (2006) on the right hand side, using our estimated firm-level collateral requirements as dependent variable. This yields similar results in terms of sign and significance of the right-hand side variables with respect to the original paper, whose coefficient are reported in the footnote. We have also calculated the original Whited and Wu (2006) measure from our balance sheet data, and found it to be positively and significantly correlated with our estimated proxy of firm-level collateral requirements.