Markups, Productivity and the Financial Capability of Firms*

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Abstract

We introduce financial frictions in a framework of monopolistically competitive firms with endogenous markups and heterogeneous productivity, as in Melitz and Ottaviano (2008). Before producing, firms pay a fixed entry cost but also need to to obtain a loan necessary to cover part of production costs. In order to obtain the loan, firms need 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, financial capability and collateral requirements enter together with productivity in the expression of the equilibrium firm-level markup. At the aggregate level, the model shows that tighter credit constraints in the form of higher collateral requirements mitigate the pro-competitive effect of trade. We test our theoretical results capitalizing on a representative sample of manufacturing firms covering 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 (a proxy of credit constraint), used to test our main proposition.

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1 Introduction

A large and growing literature shows how financial market imperfections affect country and industry-specific economic outcomes not only per se, but also through their interplay with firms' characteristics. In particular, credit constraints have been recognized as an important determinant of export and innovation activity of firms, on top of productivity.[1] In addition, there seems to be high within-industry heterogeneity of firms with respect to access to external finance, even after controlling for firm characteristics, such as size and productivity.[2]

Motivated by the latter evidence, this paper extends a framework of monopolistically competitive firms heterogeneous in productivity and with endogenous markups (as in Melitz and Ottaviano, 2008) to incorporate the presence of financial frictions. Before producing, firms pay a fixed entry cost but also need to access collateral in the form of tangible fixed 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 maximize profits, given individual productivity. To account for the heterogeneous access of firms to external finance, firms differ in their financial capability, i.e. different firms access collateral at different costs.

A novel result we obtain with this framework is that financial capability and collateral requirements enter, together with productivity, in the expression of the equilibrium firm-level markup. Another key result of the paper is that, in the industry equilibrium, higher collateral requirements mitigate the pro-competitive effects (lower markups) generally observed in standard models of trade and firm heterogeneity.

The results derived from the theoretical model are tested empirically on a representative sample of manufacturing firms covering a subset of European countries during the financial crisis (the Efige dataset).[3] For each surveyed firm in the sample we can retrieve balance-sheet information from 2002 to 2013 using the Amadeus database managed by Bureau van Dijk,

[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 in a measure for credit access (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, a feature that we also retrieve in our data. Bottazzi et al. (2008) are able to correlate a formal bank-based measure of credit rating in Italy to different measures of profitability, observing both very poor and very good firm performances in every year within the different rating classes in the same sector.

[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 items 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 well as additional firm-specific characteristics in terms of internationalization, innovation and access to finance.

We exploit these data to structurally test our model. First, starting from simple balance sheet data we back out from theory a non-parametric measure of the (ex-ante unobserved) firm-specific financial capability. We then estimate a measure of firm-specific total factor productivity (TFP) purged from the effect of financial capability, and retrieve firm-level markups following the methodology proposed by De Loecker and Warzynski, 2012.[4] We exploit the estimated financial capability, TFP and markups to structurally retrieve from the model a firm-specific measure of collateral requirements (a proxy of credit constraint), which we use to test our theoretical results.

Empirical results confirm the main propositions of the model, and are robust to a battery of sensitivity and robustness checks. The retrieved firm-level measure of credit constraints also performs well if compared to other standard proxies existing in the literature.

Our paper mainly contributes to the recent literature on international trade under credit constraints. Within the latter, Manova (2013) incorporates financial frictions and the use of collateral needed to obtain loans that cover part of fixed exports costs in a CES framework à la Melitz (2003), thus with constant markups. Peters and Schnitzer (2015) incorporate credit constraints in Melitz and Ottaviano (2008) through a model of endogenous technology adoption, in which the cost of purchasing the advanced technology has to be financed externally. In their framework, however, they assume that technology adoption results in an increase of the price margin by a fixed amount, and hence do not work out the implications of credit constraints for markups and the pro-competitive effects of trade. Egger and Seidel (2012) use again the Melitz and Ottaviano (2008) setting in order to discuss the implications of credit constraints for prices and markups, introducing the use of collateral proportional to a firm's production cost, as we do. Differently from our approach, however, they do not take into account the heterogeneity of firms in access to external finance. As a result, their profit-maximizing quantities and prices are unaffected by credit constraints, with the latter playing a role only through the cost cutoff parameter.

Another literature to which our paper is also related has started to introduce an explicit

[4]The routine for markup estimation proposed by De Loecker and Warzynski (2012) allows for flexible production technologies, being able to accomodate a different range of (dynamic or fixed) inputs of production. As the routine relies on a control for unobserved productivity, the only caveat in our model is that, with more financially capable firms obtaining fixed assets at cheaper costs, the latter might end up in the error term of the production function estimation, leading to potentially biased TFP and markup measures. To that extent we have modified the algorithms that we use to estimate productivity at the firm level (Woolridge, 2009 or Ackerberg et al., 2015), in order to control for the effects of financial capability.

role for the firm's capital structure in open economy models with heterogeneous firms. Corcos et al. (2011) build a computable equilibrium model of trade with firm heterogeneity and variable markups. In their setting, the production function of firms is a Cobb-Douglas with both labor and capital, plus productivity (Hicks-neutral technical change), under constant returns to scale. Similar to ours, they subsume the rental price of capital into the firm's marginal cost and rewrite quantity and price equilibrium equations indexing each firm by its productivity.[5]

Gopinath et al. (2015) calibrate a small open economy model with heterogeneous firms, size-dependent borrowing constraints, and capital adjustment costs to assess the importance of capital allocation in affecting productivity growth. They show how a model with financial frictions depending on firm size is better able to replicate firm behavior in the data. The latter leads to capital inflows potentially misallocated toward firms that have higher net worth, but are not necessarily more productive. While we do not look at the impact of heterogeneous financial capability on misallocation in our paper, our structural estimation of firm-level financial constraints also turns out to be significantly correlated with firm size.

Finally, our theoretical model borrows a number of insights from the financial literature, nesting them into the literature on international trade under credit constraints. From Graham et al. (1998), Vig (2013) and Brumm et al. (2015) we take the idea that the amount and quality of tangible assets collected by firms typically influence the availability of collateral that banks require as a guarantee against loans. We also exploit evidence that larger firm size is typically associated to higher (need of) loans and thus collateral, as shown e.g. by Rampini and Viswanathan (2013). Capitalizing on these findings, we model collateral as proportional to firm size and equal to a fraction of tangible assets. Banks decide the amount of collateral they require from firms: as a result, the collateral decision (the fraction of tangible assets seized by banks in case of non repayment) is exogenous to the firm, who only choose their optimal size. The latter allows us to disentangle financial capability from productivity and identify the model.

Another insight discussed in the financial literature is the relationship between the tangible assets owned by the firm and the collateral she can pledge. Tangible assets differ in terms of "redeployability" (see Campello and Giambona, 2013; Carlson et al., 2004; Zhang, 2005; Cooper, 2006; Berger et al., 2011; Cerqueiro et al., 2016). More redeployable tangible assets (eg. land) are less firm-specific, but can be more easily sold and thus are more eas-

[5] In our case, with two sources of heterogeneity, we encompass the cost of tangible assets needed to create collateral into the part of marginal costs related to the financial capability of firms, thus indexing firms by both their productivity and financial capability.

ily accepted as collateral. In our model, more financially capable firms obtain redeployable assets at different prices: as a result, these firms will benefit from a lower cost of collateral, which in turn will affect marginal costs and markups in equilibrium.

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 estimate of firm-level collateral requirements, and present our main results together with robustness checks. The final section concludes.

2 Theoretical Model

2.1 Setup and identification

We consider an economy with L consumers, each supplying one unit of labour. 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 an amount of tangible assets to be used as collateral, proportional to the overall financial needs of the firm.

Specifically, there are two types of tangible assets: redeployable (land, buildings) and non-redeployable (machinery). Redeployable assets are easier to collateralize. Firms are heterogeneous in financial capability: more financially capable firms have a lower cost of obtaining redeployable assets. Firms are also heterogeneous in marginal costs, and learn about their specific level of productivity 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, marginal costs of production and financial capability, are ex-ante uncorrelated as these are drawn from two independent probability distributions. Still, they jointly influence the firm behavior: more productive firms end up in equilibrium with higher output, require larger loans, and thus are requested a higher amount of collateral. In turn, a firm with a higher level of financial capability will face lower costs for obtaining the required amount of collateral, which will influence her overall cost structure and thus optimal production levels.

To disentangle the effects of these two sources of heterogeneity and identify the model, we exploit an empirical regularity in our data, i.e. the proportionality between firms' output and collateral (as in Rampini and Viswanathan, 2013, see infra for more detail). From this observation we can posit that firms are required by banks to collect a fixed amount of collateral per unit of output, a parameter that is exogenous from the perspective of individual firms and varies across sectors for technological reasons (as in Manova, 2013).[6] With that, we can derive an expression for the cost advantage that a firm characterized by a given level of financial capability has in creating the (exogenous) required amount of collateral per unit of output. The cost advantage is thus independent of the optimal firm size, driven by productivity. We can then rewrite firms' profits with this separable cost advantage term, and solve the model.

2.2 Demand and Production Technology

Consumers exhibit love for variety with horizontal product differentiation and quasi-linear preferences (and thus variable markups), as in Melitz and Ottaviano (2008):

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

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. 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

[6] In the second part of the paper we introduce a firm-level collateral requirement.

demand system:

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

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

On the supply side, firms use one factor of production, labour, inelastically supplied in a competitive market. The production of the homogeneous good requires one unit of labour, which implies a wage normalized to one. Both the homogeneous and the differentiated goods are produced under constant returns to scale, but entry in the latter 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.

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 $cq(c)$.[7] Banks, which operate in a perfectly competitive banking sector, define contract details for loans and make a take-it or leave-it offer to firms, specifying the collateral needed against the loan. Firms with larger output $q(c)$, having to finance a higher production cost, will require a larger volume of credit and thus would need more collateral. The latter is an empirical regularity detected in the literature (Rampini and Viswanathan, 2013) and confirmed in our data: regressing

[7] In the trade literature with credit constraints, Manova (2013) among others assumes that firms require loans to finance part of the fixed export costs; in the innovation literature, external finance is typically needed for investments that increase productivity/lower marginal costs (e.g. Peters and Schnitzer, 2015; Eckel and Unger, 2015; Gorodnichenko and Schnitzer, 2014; Mayneris, 2010). In the corporate finance literature, the external financing choice of the firm relates to the q-theory and the sensitivity of investment to cash flow (see Chen and Chen, 2012 for a summary). In the last part of the paper we model a firm-specific choice of external finance.

(log) turnover on firm's bank liabilities yields a positive and significant coefficient, i.e. larger firms require more bank loans. In turn, regressing firms' bank liabilities on tangible assets, our proxy for collateral (as in Vig, 2013 or Brumm et al., 2015), also yields a positive and significant coefficient, supporting the existence of a proportional relation between volume of output and amount of collateral pledged.[8]

Specifically, firms will be required by banks to pledge an amount of collateral proportional to the firm's output and equal to $\beta q(c)$, with $\beta > 0$. The parameter β represents the amount of collateral that banks require for each unit of output so that a loan can be disbursed to firms. The unit requirement β is chosen by the bank and varies across sectors for technological reasons, and thus it is exogenous from the perspective of individual firms.[9] Also note that 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).

The only assumption we need to make, given the imperfect nature of credit markets in our model, is that the firm, if she decides to produce, has some positive initial endowment out of which she can finance the sunk entry costs and the provision of collateral. This cash-in-advance expenses will in any case be repaid, as both will enter into expected profits in the industry equilibrium via the free entry condition.

Turning to the cost associated with collateral, we assume that the required unit amount β of collateral is allocated by firms across different types of tangible fixed assets.[10] In particular the literature has identified two different categories of tangible assets that firms can use as collateral (Campello and Giambona, 2012): redeployable assets (Re) constituted by land, plants and buildings; and non-redeployable assets (NRe), e.g. machinery and equipment. Redeployable assets are easier to resell on organized markets: being more liquid, they can be easily used as collateral and thus facilitate firms' borrowing. Non-redeployable assets

[8]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.

[9]Under asset-based lending, collateralizable assets include inventory, accounts receivable, machinery and equipment, real estate or the cash flow. All these assets can be modeled as a generic function of a firm's output. In Manova (2013) a fraction of the sunk entry cost into export goes towards tangible assets that can be used as collateral. Our results hold with any general specification of a functional form for the unit requirement of collateral, as long as it is exogenous to firms. In the last part of the paper we also model a firm-specific collateral requirement.

[10]The use of tangibles as collateral for loans is a standard practice for firms asking for loans and a common feature of the finance literature, as discussed among others by Graham (1998), Vig (2013) or Brumm et al. (2015). The fact that larger firms also have more tangible assets is another well known stylized fact. Manova (2013) assumes that a part of the sunk export entry cost goes toward tangible assets that firms can use as collateral.

are more firm-specific and with a value that deteriorates over time (because of technological obsolescence): as such, they are less easy to be used as collateral.

Firms are heterogeneous in their financial capability of negotiating the price of redeployable assets. Specifically, firms are characterized by a specific level of financial capability $\tau \in [0, 1]$ randomly drawn from a probability distribution and independent of $c \in [0, c_M]$. The price of redeployable assets Re is thus $1 - \epsilon(\tau)$, with $\epsilon(\tau) \geq 0$ and increasing in τ.

The intuition here is that firms with better financial expertise can fetch a lower price on the market for their redeployable assets. This is in line with evidence provided by Guner et al. (2008), showing how e.g. the financial expertise of directors plays a positive role in finance and investment policies adopted by the firm. Glode et al. (2012) also model the financial expertise of firms as the ability in estimating the value of securities, and show how these characteristic increase the ability of firms of raising capital.[11] The price of non-redeployable assets instead can be normalized at unity. In fact, as these assets tend to be firm-specific in their use, one can assume that part of their price is formed on perfectly competitive markets plus an idiosyncratic component characterizing each firm, ultimately subsumed in the marginal production cost c.

To model the optimal allocation between redeployable and non-redeployable assets, given the constraint on the required unit amount of collateral, we use a generic CES function resulting in the following minimization problem:

$$\min C(Re, NRe) = (1 - \epsilon(\tau))\, Re + NRe \tag{5}$$

subject to the constraint:

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

The term $C(Re, NRe)$ represents the cost of tangible asset per unit of output that the firm spends when allocating its endowment in redeployable (Re) and non-redeployable (NRe) assets, given the price of the same assets, with $\delta \in [0, 1]$ and $\sigma > 1$ being respectively the input share and elasticity of substitution between (Re) and (NRe). The constraint β is the

[11] Alternatively, one can think at the relationship lending literature, studying how the relationship of managers with banks increase funds availability and reduce loan rates (see Elyasiani and Goldberg, 2004, for a review of the literature). More financially capable managers might be more skilled in bargaining with banks, thus reducing the overall cost of collateral needed to obtain a given loan. The channel through which these effects can have an impact on firms lending are both fund availability and quantity (see Boot and Thakor, 1994; Berger and Udell, 1996; Cole et al., 2004), or prices and collateral (see Berger and Udell, 1998; Petersen and Rajan, 1995).

amount of collateral per unit of output required by banks.

From the minimization of the cost function (5) we obtain

$$C(\tau) = \frac{\beta\left(1-\epsilon(\tau)\right)}{\left[\delta^{\sigma} + (1-\delta)^{\sigma}\left(1-\epsilon(\tau)\right)^{\sigma-1}\right]^{\frac{1}{\sigma-1}}} \tag{6}$$

which is the expenditure function computed in the optimal amount of redeployable and non-redeployable assets for a firm with a level τ of financial capability, and a β unit requirement for collateral.As such, $C(\tau)$ is the marginal cost of collateral and is strictly decreasing in the financial capability τ of the firm for $\delta > 0$.[12]

From Equation (6) it is possible to define the financial capability cutoff, i.e. the level of financial capability that makes firms indifferent (in terms of costs) in allocating their endowment between *Re* vs. *NRe* assets. This corresponds to $\widetilde{\tau}$ such that $\epsilon(\widetilde{\tau}) = 0$, i.e. a firm characterized by the (cutoff) financial capability $\widetilde{\tau}$ would not obtain any type of advantage in the price of redeployable assets. The latter represents the upper bound in the marginal cost of collateral and is equal to:

$$C(\widetilde{\tau}) = \beta\left[\delta^{\sigma} + (1-\delta)^{\sigma}\right]^{-\frac{1}{\sigma-1}} \tag{7}$$

The implications of heterogeneity in financial capability can be seen considering the case of all firms having the same financial expertise $\bar{\tau}$. As firms in the industry have the same unit requirement β, in our setting they will end up with the same marginal cost of collateral $C(\bar{\tau})$. In this case, the total cost of collateral $\overline{TC}(c) = C(\bar{\tau})q(c)$ will be just a function of the firm's size, i.e. ultimately of its marginal production costs c. In other words, even introducing financial constraints in our framework, without heterogeneity in financial capability we will have that productivity is the only endogenous variable needed to characterize the entire equilibrium of the industry: a given marginal cost c would in fact determine the firm's size $q(c)$ and from here the volume of the loan as a share ρ of production costs $cq(c)$, as well as the total cost $\overline{TC}(c)$ of the collateral (via the parameter β) to pledge against these loans. Introducing heterogeneity also on financial capability τ, on top of productivity, allows instead to derive non-trivial implications for firms' behavior, especially when studying the implications of financial shocks.

[12]Once again, our results hold with a more general specification of a functional form for the unit requirement and the cost of collateral, as long as $\partial C(\tau)/\partial\tau < 0$.

2.4 Banking sector

Firms that fund a share ρ of their total production costs $cq(c)$ have to repay $R(c)$ to banks. Repayment occurs with exogenous probability λ, with $\lambda \in (0,1]$, which is exogenously determined by the strength of financial institutions; with probability $(1-\lambda)$ the financial contract is not enforced, the firm defaults, and the creditor seizes the start-up capital $\beta q(c)$.[13]

To close the deal, the participation constraint of a bank is then:

$$-\rho c q(c) + \lambda R(c) + (1-\lambda)\beta q(c) \geq 0 \tag{8}$$

As we can easily see, no interest rate is charged by banks because of perfect competition in the banking sector. For the same reason, the participation constraint holds with equality for all banks. Hence, it is possible to derive an expression for the repayment function:

$$R(c) = \frac{1}{\lambda}[\rho c - (1-\lambda)\beta]q(c) \tag{9}$$

Moreover, although all firms with a financial capability larger than $\widetilde{\tau}$ can in principle obtain a loan, firms will apply only 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 (see e.g. Manova, 2013). In evaluating this constraint in our setting, we should also consider the heterogeneity of firms in terms of the costs incurred to raise the required startup capital.

Hence, we derive an expression for the cost advantage that a firm characterized by financial capability τ will have in creating the required amount of startup capital with respect to the cutoff firm. By substracting (6) from (7) we get

$$\theta(\tau) = C(\widetilde{\tau}) - C(\tau) = \beta[\nu(1-\eta(\tau))] \tag{10}$$

with $\eta(\tau) = [(1-\epsilon(\tau))^{\sigma-1}]^{-\frac{1}{\sigma-1}}$ and $\nu = [\delta^{\sigma} + (1-\delta)^{\sigma}]^{-\frac{1}{\sigma-1}}$. Equation (10) is increasing in τ and describes the cost advantage of a firm with financial capability τ. As it can be easily seen, the financial capability cutoff firm characterized by $\epsilon(\widetilde{\tau}) = 0$ will have no cost advantage, i.e. $\theta(\widetilde{\tau}) = 0$.

From here, we can write the liquidity constraint of the firm, now incorporating the two sources of firm heterogeneity in marginal costs and financial capability (c, τ)

[13] Note that banks would supply give loans to all firms characterized by a financial capability above the cutoff, as all these firms are able to raise start-up capital.

$$p(c,\tau)q(c,\tau) - (1-\rho)cq(c,\tau) + \theta(\tau)q(c,\tau) \geq R(c,\tau) \quad (11)$$

A firm for which the above inequality does not hold would not be able to obtain the loan because of its inability to reimburse the debt to the borrower. This firm would exit the market right after the entry, i.e. after the random draw of its τ and marginal cost of production c.

2.5 Profit maximization

Each firm in the differentiated sector maximizes the following profit function

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

As there are two sources of heterogeneity (c and τ), to solve the model we have to consider the cutoff level of marginal costs at which profits are zero (a free exit condition, as in Melitz and Ottaviano, 2008), given the cost advantage in generating startup capital obtained by a firm with financial capability τ with respect to the cutoff $\widetilde{\tau}$, and under the participation constraint (8), the liquidity constraint (11) and the demand for the supplied variety (3).

By plugging the expression for repayment (9) in the profit function, and substituting the generic expression of costs $C(\tau)$ with the cost advantage $\theta(\tau)$, we obtain a much more tractable form for firm's profits, in which the financial capability cutoff is already incorporated:

$$\pi(c,\tau|\widetilde{\tau}) = p(c,\tau)q(c,\tau) - cq(c,\tau) + \theta(\tau)q(c,\tau) \quad (12)$$

Solving the profit maximization problem and using the demand constraint (3) to derive $\frac{\partial p}{\partial q} = -\frac{\gamma}{L}$ yields the FOC:

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

By rearranging the terms in the above equation, we obtain the supply condition:

$$q(c,\tau) = \frac{L}{\gamma}\left[p(c,\tau) - c + \theta(\tau)\right] \quad (13)$$

We can now use the liquidity constraint (11) in order to impose a free entry condition and derive the marginal cost cutoff c_D. Knowing that firms that would not be able to repay the debt will directly exit the market, the liquidity constraint must hold with equality for the cutoff firm. Moreover, since the cutoff firm corresponds to that firm that sets $p_i = p_{max}$, we can rewrite (11) as follows:

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

Rearranging the terms in the equation above yields a simple expression for p_{max} as a function of the cost cutoff c_D:

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

where $\omega=\frac{\rho}{\lambda}+1-\rho$ and $\phi=\frac{1-\lambda}{\lambda}\beta$ are constants.

Note that, since $\theta(\tau)$ is increasing in τ, the maximum price charged by a firm corresponds to the price made by the least financially capable firm, since $\theta(\widetilde{\tau})$ is the lower bound of $\theta(\tau)$. For this reason, in correspondence of p_{max} we have that $C(\tau)=C(\widetilde{\tau})$. Therefore we have:

$$p_{max}=\omega c_D-\phi \tag{14}$$

2.6 Equilibrium

At equilibrium, the demand for each variety equals supply:

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

As the first two terms on the left hand side are equal to p_{max}, by substituting it with its expression in (14) and rearranging we obtain the equilibrium price charged by a firm characterized by a given set of (c,τ)

$$p(c,\tau)=\frac{1}{2}\left[\omega c_D+c-\phi-\theta(\tau)\right] \tag{15}$$

From here, we can derive an expression for the equilibrium markup of a (c,τ)-firm by subtracting the marginal cost from the equilibrium price:

$$\mu(c,\tau)=p(c,\tau)-MC(c,\tau)=\frac{1}{2}\left[\omega c_D-c-\phi+\theta(\tau)\right] \tag{16}$$

By looking at expression (16), it is easy to note that, 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. Hence, the more productive a firm, the higher would be its markup (holding constant the effects on the equilibrium cost cut-off c_D of the industry, herein discussed).

Differently from Melitz and Ottaviano (2008) however the introduction of credit constraints, as well as a second source of firm heterogeneity, namely financial capability in raising startup capital, affect the expression of the markup. First, from eq. (16) is clear that a higher financial capability translates, *ceteris paribus*, into a higher markup, via the effect of the cost advantage $\theta(\tau)$. The intuition is that a higher financial capability leads to a higher cost advantage in generating the required amount of startup capital: similar to productivity, more financially capable firms then transfer this advantage into a markup premium. As a result, conditional on the existence of credit constraints / collateral requirements, the dispersion of firm-level markups around a productivity level normally observed in the data could be explained by this second source of firm heterogeneity.[14] To validate this hypothesis, in the second part of the paper we will empirically test on firm-level data the following

Proposition #1. *The equilibrium markup $\mu(c,\tau)$ of a firm characterized by a pair (c,τ) is ceteris paribus an increasing function of financial capability τ.*

The second change brought about by our model to the expression of the firm-level markup is the role of collateral requirement β, that enters in the expression of the parameter ϕ, the cut-off c_D and the cost advantage $\theta(\tau)$. To understand how a change in credit constraints affects firm behavior, we thus need to solve for the industry equilibrium.

2.7 Parameterization

To fully characterize the industry equilibrium, we have to solve for the value of the cost cut-offs c_D and $\widetilde{\tau}$. As in Melitz and Ottaviano (2008), we assume that the marginal cost of production c follows an inverse Pareto distribution with a shape parameter $k \geq 1$ over the support $[0, c_M]$. As we have no ex-ante prior on the distribution of financial capability of firms, we assume that τ follows a uniform distribution in the interval [0,1]. The cumulative density functions of c and τ can then be written as:

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

$$F(\tau) = \tau \text{ with } \tau \in [0, 1]$$

[14] Given the independence of the two distribution of costs and financial capability, we can consider the cost cut-off c_D as given in analyzing the effect of τ on the markup.

respectively. The density functions are $g(c) = \frac{kc^{k-1}}{c_M^k}$ and $f(\tau) = 1$. The distributions of surviving firms, once that productivity and financial capability have been drawn by firms, are still an inverse Pareto and a Uniform, and the densities are therefore equal to $g(c) = \frac{kc^{k-1}}{c_D^k}$ and $f(\tau) = \frac{1}{1-a}$.

Under these assumptions, it is possible to solve for the financial capability cutoff $\widetilde{\tau}$, independently from c_D. Recall that the cut-off of τ is defined as $\epsilon(\widetilde{\tau}) = 0$. We thus need to specify a functional form of $\epsilon(\tau)$, i.e. the price advantage enjoyed by the τ firm in the purchase of the redeployable asset. We assume that $\epsilon(\tau) = \tau - a$, with $a \in [0, 1)$ being a constant. It is easy to note that $\epsilon(\tau)$ increases in τ and the function equals 0 in correspondence of a, therefore implying that the financial capability cutoff is $\widetilde{\tau} = a$.[15]

To solve for the cost cut-off c_D we need to apply the free-entry condition, defined over both sources of heterogeneity. From the equality of demand and supply we can derive an expression for a firm's profits in equilibrium:

$$\pi(c, \tau) = \frac{L}{4\gamma} \left[\omega c_D - c - \phi + \theta(\tau)\right]^2 \tag{17}$$

Firms would be willing to enter the market until expected profits are equal to the fixed cost of entry f_E, i.e.:

$$\pi^e = \int_0^{c_D} \int_a^1 \frac{L}{4\gamma} \left[\omega c_D - c - \phi + \theta(\tau)\right]^2 \, dF(\tau) \, dG(c) = f_E \tag{18}$$

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

$$\pi^e = \frac{Lk}{4\gamma c_M^k} \int_0^{c_D} \int_a^1 \left[\omega c_D - c - \phi + \theta(\tau)\right]^2 c^{k-1} \, d\tau \, dc = f_E \tag{19}$$

As shown in Appendix A, it is not possible to find an explicit solution for c_D in (19). However, as shown in the same Appendix, one can prove that a positive solution always exists and it is unique conditional on a choice of c_M. The parametrization then allows us

[15]The assumption of a uniform distribution of τ together with its independence from marginal costs c (as the allocation problem of tangible assets is not related to productivity) implies that the financial capability cutoff $\widetilde{\tau}$ does not depend on market characteristics but rather is a constant, whereas the cost cutoff c_D is endogenous like in Melitz and Ottaviano (2008). This simplification allows to control for a second source of heterogeneity in the firm-level equilibrium equations, while maintaining the model tractable at the level of industry aggregates. The latter does not entail however a loss of generality, as it can be shown that for relevant shocks (e.g. market size) the effects of the cost and financial capability cutoffs go in the same direction.

to find an expression for the equilibrium number of firms in the market and derive average performance measures as a function of c_D.[16]

By equating both expressions (4) and (14) for p_{max} and solving N, we obtain

$$N = \frac{\gamma}{\eta} \frac{(\alpha - \omega c_D + \phi)}{(\omega c_D - \phi - \overline{p})} \tag{20}$$

which corresponds to the number of firms, and therefore varieties of the differentiated good, active in the market in equilibrium. From here we can derive an expression for the average price for the differentiated good and obtain a parameterized expression also for N.

Since the average price is a function of the the average marginal cost and financial capability, we first derive expressions for these measures. Following Melitz and Ottaviano (2008), we define the average marginal cost of production as:

$$\overline{c} = \frac{\int_0^{c_D} cg(c)dc}{G(c_D)} = \frac{kc_D}{k+1} \tag{21}$$

Since the financial capability τ is distributed as a uniform over the interval $(0, 1)$, we also have that:

$$\overline{\tau} = \frac{\int_a^1 \tau f(\tau)d\tau}{F(1-a)} = \frac{1+a}{2} \tag{22}$$

Now we can derive an expression for the average markup charged by firms active in the market, which corresponds to:

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

Solving the integral yields:

$$\overline{\mu} = \frac{1}{2} \left[\frac{\omega k + \omega - k}{k+1} c_D - \phi + \beta \left(\frac{1}{1 - 2\delta + 2\delta^2} - \frac{1}{(\delta - 1)^2} ln \left(\frac{1 - 2\delta + 2\delta^2}{a(\delta - 1)^2 + \delta^2} \right) \right) \right] \tag{23}$$

which can be rewritten as

$$\overline{\mu} = \frac{1}{2} \left[\frac{\omega k + \omega - k}{k+1} c_D - \beta\psi \right] \tag{24}$$

where the constant $\psi = \frac{1-\lambda}{\lambda} - \frac{1}{1-2\delta+2\delta^2} + \frac{1}{(\delta-1)^2} ln \left(\frac{1-2\delta+2\delta^2}{a(\delta-1)^2+\delta^2} \right) > 0$, implying a direct negative effect of collateral requirements on the average markup.

[16]The limitation of the setup is that the effect of the variable of interest (say market size) on a given performance measure (say markup) cannot be solved numerically, but will have to be assessed by taking into account the sign of the effect of the variable of interest on c_D.

2.8 Trade shock and the role of financial constraints

Our setup allows us to analyze the effects of an increase in the market size L, which is analogous to a symmetric opening of the economy to trade as in Melitz and Ottaviano (2008). Differentiating equation (24) yields

$$\frac{\partial \overline{\mu}}{\partial L} = \frac{1}{2}\left[\frac{\omega k + \omega - k}{k+1}\frac{\partial c_D}{\partial L}\right] < 0$$

To explore the implications of a trade shock we thus have to look at the effect of an increase in L on the cost cutoff c_D. As shown in Appendix B, we have that $\frac{\partial c_D}{\partial L} < 0$, 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 effect of trade identified in the literature.[17]

Still, a closer look at the expression for the average markups reveals that financial constraints can play a role in the reaction of the economy to a trade shock. In fact, the magnitude of the derivative of the cost cutoff with respect to L depends, among others, on the amount of collateral requirements β (see Appendix B for a discussion). In particular, when β is relatively large, i.e. when banks require more collateral for the same loan, the effect of a change in L on the cost cutoff is relatively low.[18] We can formalize this finding with the following

Proposition #2. *An increase in the market size L lowers the average markup $\overline{\mu}$. Tighter credit constraints in the form of higher collateral requirements tend however to mitigate the pro-competitive effect of trade.*

3 Data and estimations

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 (FP7/2007-2013). The project aims at analyzing the competitive performance of European

[17]Given the assumption of $\widetilde{\tau} = \alpha$ being independent of market characteristics, financial capability does not affect the reaction of average markups to a trade shock. Extending the model to the case of an endogenous financial capability cutoff, i.e. solving the free entry condition also for $\widetilde{\tau}$, would still yield a pro-competitive effect of trade on average markups also through the financial capability channel.

[18]The ECB Bank Lending Survey shows how in the years 2008 and 2009 collateral requirements by banks have tightened threefold in the euro area.

firms in a comparative perspective. This dataset is the first harmonized cross-country dataset containing quantitative as well as qualitative information on around 150 items for a representative sample of some 15,000 manufacturing firms in the following countries: Austria, France, Germany, Hungary, Italy, Spain, and the United Kingdom. The firm-level variables observed in the dataset cover international strategies, R&D, innovation, employment, financing and organizational activities of firms, before and after the financial crisis.[19]

The firm-level information present in the Efige dataset has been matched with balance sheet information drawn from the Amadeus database managed by Bureau van Dijck, retrieving twelve years of usable balance-sheet information for each surveyed firm, from 2001 to 2013. Overall, the dataset includes representative samples of about 3,000 firms operating in Germany, France, Italy and Spain, some 2,200 firms in the United Kingdom, and about 500 firms for Austria and Hungary, as reported 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 sampling design follows a stratification by industry, region and firm size structure. Firms with less than 10 employees have been excluded from the survey, that instead presents an oversampling of larger firms with more than 250 employees to allow for adequate statistical inference for this size class. Descriptive statistics are reported in Appendix C.[20]

[19]The complete questionnaire is available on the Efige web page, www.efige.org. A discussion of the dataset as well as its validation is available in Altomonte et al (2012), while Bekes et al. (2011) discuss explicitly the reaction of firms to the crisis as measured in the survey.

[20]In order to take into account the oversampling and to retrieve the sample representativeness of the firms' population, a weighting scheme (where weights are inversely proportional to the variance of an observation) is set up according to firm's industry and class size. All our regression results are thus computed by taking into account this weighting scheme, except where otherwise specified. Detailed information on the distribution of firms by country/size class and industry can be retrieved on the Efige website.

3.2 Estimation of financial capability

The theoretical model allows to back out an estimate of the cost advantage $\theta(\tau)$ deriving to each firm from (unobserved) financial capability τ simply relying on balance sheet information. The starting point is to write an expression of the total amount of tangible assets (then used by each firm as collateral) in nominal terms. Recalling that $C(\tau)$ in equation (6) represents the marginal cost of collateral, and that collateral is proportional to a firm's output, then the nominal value of tangible assets TA observed in a firm's balance sheet can be written as $TA(\tau, q) = C(\tau)q(c, \tau)$. The latter implies that the nominal value of a firm's tangible assets should be decreasing in τ (as $C(\tau)$ is decreasing in τ) once controlling for firm size. The intuition here is that all firms are required to collect the same amount β of TA per unit of output, but firms with higher τ will obtain that required amount at a lower cost (lower nominal value). Also, for the cut-off firm $\tilde{\tau}$ we have $TA(\tilde{\tau}, q) = C(\tilde{\tau})q(c, \tau)$. It then follows that the nominal value $TA(\tilde{\tau}, q)$ represents the highest value of tangible assets owned by a (cutoff) firm of size $q(c, \tau)$.[21]

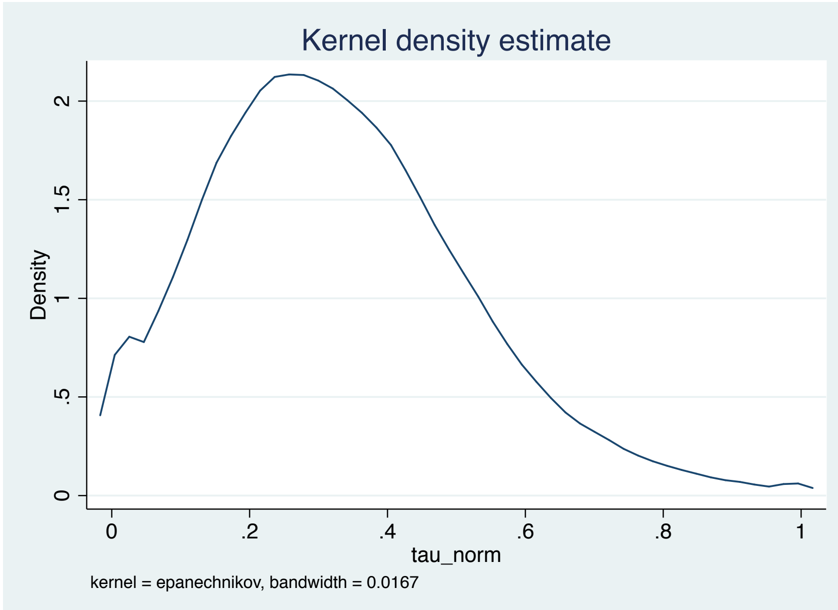
From here we can estimate $\theta(\tau)$ non-parametrically in three stages. First, we create size ranges of firms, by industry (deciles, and then quintiles and twentiles as robustness). Secondly, for each size range within each industry, we identify the upper bound level of (nominal) tangible assets recorded by firms (average TA of top 5% of firms, robustness with 1%): this value of TA represents the TA level of the cut-off firm(s). Finally, we compute the firm-specific $\theta(\tau)$ by dividing the TA level of the cut-off firm for each firm-level value of nominal TA, for every size/industry partition. We retrieve an index ≥ 1 which we then bound between 0 (cutoff firms) and 1 (maximum financial capability).[22] The estimated distribution of $\theta(\tau)$ is left-skewed, as we can see in Figure 1.

Considering all combinations of size ranges (quintiles, deciles, twentiles) and of cutoff levels of tangible assets (1%, 5%), we obtain several version of our firm-specific cost advantage measures, which we will use as sensitivity checks in testing our Propositions.

[21] Recall that $C(\tilde{\tau})$ is the upper bound of the cost function each firm has to face while investing in a given amount of tangible assets.

[22] Our identification strategy crucially relies on the fact that financial capability and productivity / marginal costs are independent, as a correlation would result in biased measures. While we will explicitly purge total factor productivity estimates from the effects of financial capability, the firm-level measure of $\theta(\tau)$ retrieved here is in any case uncorrelated (.008) with the firm-level labor productivity (value added per employee) measured in the sample.

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



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, DLW), who estimate markups combining the output elasticity on a input as obtained from the estimation of a production function, 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 allows for production technologies that can accommodate different types of variable or fixed inputs of production. Second, the DLW estimate of the correlation between markups and firm-level characteristics is not affected by the availability of real vs. nominal output (revenue) data, thus allowing us to test our Propositions using the same balance sheet information from which we have retrieved our measure of financial capability.[23]

Still, although the correlations retrieved with DLW-estimated markups are robust to the omitted price variable bias, standard estimates of the production function might lead to a spurious correlation between two variables driving markups in our structural model, namely TFP and financial capability. The reason is that more financially capable firms can obtain fixed assets at a lower cost: if the latter is not controlled for in the estimation of the production function, this ends up in the retrieved TFP term inducing multi-collinearity with

[23]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 prices impacts only the estimate level of the markup, not its correlation with firm characteristics.

financial capability in our estimated Equation (16). For these reasons, we have modified the algorithms generally used to estimate TFP so as to include financial capability as an additional control (as in De Loecker, 2007, for the export status).

Technically, we have estimated our production function coefficients relying on Wooldridge (2009), which proposes to improve on the Ackerberg, Caves and Frazer (ACF-2015) algorithm originally employed in De Loecker and Warzynski (2012) through the use of a GMM framework. We have then used these estimated coefficients (with and without correction for financial capability) to compute firm level markups, as well as total factor productivity estimates. Table 2 below reports the median values and standard deviations of four different firm-level markups computed by using our TFP measures. The first two employ the Woolridge (2009) algorithm for computing TFP, both in the standard and corrected version discussed above. As a sensitivity check, we have estimated production function coefficients through the ACF-2009 routine, and then used the retrieved coefficients to construct an alternative measure of markups which replicates De Loecker and Warzynski (2012). The fourth estimate reports markups estimated via the ACF algorithm corrected for financial capability. We will employ these different measures to provide additional robustness checks of our test of Proposition I.

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 Test of Proposition 1

The model predicts that, conditional on firm-level productivity, a higher financial capability τ is associated to higher markups, as financially more capable firms, ceteris paribus, are able to generate redeployable assets (primarily used as collateral) at cheaper costs, a gain then reflected in their markups. Specifically, recalling our markup equation (16)

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

we structurally estimate the latter at the firm-year level, with the dependent variable $\mu(c,\tau)$ being the markup estimated through De Loecker-Warzynski (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 TFP measure, corrected for τ and previously estimated, while $\theta(\tau)$ is the (normalized) non-parametric estimation of the level of financial capability retrieved as described in section 3.2.

We test equation (16) 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 (as in this case the markup is influenced by the lower cost of the required startup capital), we always condition our estimates on whether firms have requested in the considered period a loan from a bank, an information available in our dataset.[24]

Table 3 presents our benchmark results, in which we estimate firm-specific financial capability by deciles of sales, and we assume the cutoff level of tangible assets to be the top 5% for each 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.[25] Results confirm that markups are positively correlated with productivity and that even controlling for productivity 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 at the firm level (and thus not picked up by our firm FE) might drive the results, introducing as additional control the country-time specific change in collateral requirement as retrieved from the ECB Bank Lending Survey for the euro area.[26]

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 through the between variation in the data: controlling for productivity, firms with higher financial capability should also have higher markups. 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

[24] As a matter of fact, this condition is verified for 14,139 firms in our data, i.e. 96% of the sample.

[25] In terms of our structural estimation, firm-level fixed effects subsume the parameters ωc_D and ϕ.

[26] The ECB Bank Lending Survey shows in fact how in the years 2008 and 2009 collateral requirements by banks have tightened threefold on average in the euro area.

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	$\ln(\mu)_i$	$\ln(\mu)_i$	$\ln(\mu)_i$	$\ln(\mu)_i$
$\ln(TFP)_i$	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, assuming firms having top 5% of TA to be the cutoff firms. TFP is (in log) 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.

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 a firm's size, variables that are known to exert an impact on on TFP and financial constraints (see for example Hadlock and Pierce, 2010).[27] 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 (the year for which we can add as controls additional firm characteristics observed in our survey, see Table (4) infra). In both these 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 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 τ. Namely, in row (1) we estimate financial capability 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 to twentiles, and narrowing the cutoff level of tangible assets to the top 1% of the distribution in each NACE2-year. In rows from (3) to (5) we replicate the three different estimation method of our benchmark Table 3 (FE, BE and 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 confirmed, with little changes in magnitude with respect to our benchmark results.

In a second group of sensitivity checks (rows 6 to 8), we go back to our benchmark measure of financial capability, but we experiment with the methods through which markups have been estimated, in order to avoid picking up some spurious correlation deriving from the estimation method itself. In row (6) we employ markups retrieved from TFP measures estimated with the ACF (2015) method and the correction for financial capability; in row (7) we replicate the results with markups estimated from TFP calculated through the standard Woolridge (2009) algorithm, i.e. not corrected for financial capability; in row (8) we repeat the exercise for the ACF(2015) estimates, with markups retrieved from TFP again not

[27]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 employee to the size categories.

corrected for τ, thus being as close as possible to the original De Loecker and Warzynski (2012) approach. Once again the sign and significance of our key parameters is confirmed.

Rows (9) to (12) of Table (4) present a number of robustness checks on the cross-section specification (column 4 of Table 3). The purpose is to assess whether our measure of financial capability keeps its significance also when controlling for unobservables 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 inquires on 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 relatively cheap cost of collateral (thus a higher τ) 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 correlation between financial capability and markups potentially driven by an omitted variable. 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) show that markups differ dramatically between exporters and nonexporters, 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 results remain unchanged.

4.2 Test of Proposition 2

Our second theoretical result points at the fact that a trade shock leads, on average, to pro-competitive effects of trade mediated by credit constraints, with larger collateral requirements leading to lower reductions in average industry markups. To test for this, we estimate our markup equation now augmented with a trade shock measured at the country, industry and year level, and a proxy of firms' collateral requirements (or credit constraints) β_i that we have to derive from our model.

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 (no correction)	1.575***	(0.0137)	1.283***	(0.0260)	35,565	0.825
(8) Markups ACF (no 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. Model specification as in columns (2) to (4) of Table 3. All estimates with robust standard errors.

First, we build a variable that measures the sudden, ample and symmetric negative trade shock incurred by European countries during the credit crisis of 2008/09 (Baldwin, 2009). Starting from BACI trade data at the country-industry-year level, we create a dummy variable T_{zjt} that takes value of 1 if the yearly growth of a given zj trade flow in each country-industry pair is in the bottom 25% of the overall growth rate distribution observed for the years 2007-2010.

Second, we structurally derive from our model a proxy for firm-specific collateral requirements. We start from our equation (10) describing the cost advantage of a firm with financial capability τ. With firm-specific collateral requirements β_i, the latter expression becomes

$$\theta(\tau, \beta) = \beta_i[\nu(1 - \eta(\tau))]$$

as we do not posit ex-ante a specific collateral requirement for the cut-off firm $(\widetilde{\tau}, c_D)$.[28] It then follows that our markup equation (16) incorporates an additional source of heterogeneity related to the firm-specific collateral requirement

$$\mu(c, \tau, \beta) = \frac{1}{2}\left[\omega c_D - c - \phi + \theta(\tau, \beta)\right] \tag{25}$$

[28]Banks might be unable to identify the cut-off firm, or might base their firm-specific collateral requirement decisions on financial variables unrelated to financial capability or productivity.

The latter can again be estimated in its structural form, with β_i now entering in the error term of the estimation.[29] In particular, estimated $\hat{\beta}_i$ are derived as the (normalized and inverted) residuals of the estimation of equation (25), run separately for each industry and including firm and year fixed effects. Note that function ϕ is increasing in β, which, in this case, is the constant sector-level measure of financial constraints, which justifies the by sector estimation of the structural equation. A plausibility check, reported in Appendix D, shows a good correlation between our estimated $\hat{\beta}_i$ and other standard measures of firm-level credit constraints existing in the literature.

Based on the theoretical model, we should observe a positive sign of the trade shock dummy, as a negative trade shock leads to higher markups. We should also observe a negative sign of the firm-specific collateral requirement: the intuition for the latter result is that when banks pledge for more collateral, at the firm level this increases costs, and thus leads to a reduction of markups. At the industry level, 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 would not obtain the loan from banks and exit, generating a fall in the production cost cutoff c_D, and thus a reduction in average markups. Finally, if our Proposition 2 is correct, we should also observe a negative sign of the interaction between the trade shock and the collateral requirement, as Proposition 2 states that the effect of the trade shock should be smaller the higher is the collateral requirement.

Table 5 reports the results of our estimation for the time window 2006-2009.[30] 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 situation 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 and size). Moreover we always employ bootstrapped standard errors, as we use an estimated proxy for firm-specific collateral requirements.

In column (1), markups, TFP and financial capability are defined as in our benchmark specification (Table 3). The (country-industry-year) negative trade shock and the firm-specific collateral requirements are measured as described above. Results are in line with our prediction: on top of the standard sign and significance of TFP and financial capability, a negative trade shocks leads to higher markups, while higher firm-specific collateral requirements lower them. Most importantly, the interaction between the trade shock and

[29] Firms with (ex-ante unobserved) higher collateral requirements should have lower markups, i.e. negative residuals from the difference between observed and predicted markups.

[30] We have obtained similar results with the window 2007-2010.

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 (in log) computed through a modified version of Wooldridge (2009), cleaning production function estimates for firm-level financial capability in columns 1, 2, 3, 5, and modified version of Ackerberg, Caves and Frazer (2015) in columns 4. Negative trade shock is a dummy=1 if the yearly growth of a given trade flow in a country*industry*year is in the bottom 25% of the overall growth rate distribution observed for the years 2007-2010. Collateral requirement is our $\hat{\beta}_c$ estimated from equation (25) and normalized. All specifications are estimated with bootstrapped standard errors (1,000 reps).

the collateral requirement is negative and significant, in line with Proposition 2.

In columns (2) to (5) we provide a number of robustness check of this result. In column (2) we recompute our results using 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 variables markups estimated through the ACF(2015) algorithm. Finally, in column (5) we use as a measure of firm-level financial constraints a dummy taking value 1 if a firm is above the median estimated $\hat{\beta}_c$. All our results hold.

5 Conclusions

In this paper we have introduced financial frictions in a framework of monopolistically competitive firms with endogenous markups and heterogeneous productivity, as in Melitz and Ottaviano (2008). Before producing, firms need to invest part of their fixed costs in start-up capital to be used as collateral in order to obtain a loan necessary to finance production costs. In addition to productivity, firms are also heterogeneous in their financial capability: some firms obtain start-up capital at better conditions, thus decreasing their cost of collateral.

The theoretical model predicts that, conditional on productivity, a higher financial capability is associated to higher markups at the firm level, while higher collateral requirements mediate the pro-competitive effects of trade shocks on average across firms. These theoretical results are structurally tested on a representative sample of manufacturing firms covering a subset of European countries during the financial crisis. Through the theory we also obtain a structural non-parametric measure of firm-level financial capability from balance sheet information, through which we can derive TFP measures unbiased for the (unobserved) capital formation process. Our framework allows us to derive a structural measure of credit constraints at the firm level, that we used in firm-level analyses of the impact of financial frictions on the industry equilibrium.

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Appendix

A Existence and uniqueness of cost cutoff

Equation (19) 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 $f'(c_D)$. Hence, if $f'(c_D) = 0$ at least two positive values of the cost cutoff exist. 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

$$f'(c_D) = (k+2)A c_D^{k+1} + (k+1)B c_D^k + kC c_D^{k-1}$$

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 $f(c_D) = 0$.

B Derivative of cost cut-off with respect to L

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 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 A. The denominator is instead equal to:

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

and is positive as well, consistent with the fact that a larger cutoff leads to larger profits in expectations for firms which are not in the market yet, as even a less productive firm would be able to gain from entry. 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 β affect the above derivative, we have that a higher β will translate *ceteris paribus* into a lower value of $\frac{\partial c_D}{\partial L}$ for a broad range of parameters, considering that financial constraints in the current framework are to be interpreted as shadow price of collateral, which implies that $\beta > 1$.

C Descriptive statistics

Table 6 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 6: 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

D 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, 2015), we provide simple correlations between one of the existing proxies of collateral requirement as derived from balance sheet data in the literature, and our measure.

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. The specification of the Whited and Wu index and the estimated coefficients are as follows:

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

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.

The WW measure retrieved from our balance sheet data is positively and significantly correlated with our estimated proxy of firm-level credit requirements. Also, regressing both measures against firms' profit margins, including firm and year fixed effects, yields a negative and significant coefficients in both cases. Moreover, replicating the Whited and Wu (2006) equation reported above using our estimated firm-level collateral requirements as dependent variables yields similar results in terms of sign and significance of the right-hand side variables, as reported in the Table below.

Table 7: Replication of Whited and Wu (2006) equation

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