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# Markups, intangible capital and heterogeneous financial frictions

Carlo Altomonte
Domenico Favoino
Monica Morlacco
Tommaso Sonno

**Abstract**
This paper studies the interaction between financial frictions, intangible investment decisions, and markups at the firm level. In our model, heterogeneous credit constraints distort firms' decisions to invest in cost-reducing technology. The latter interacts with variable demand elasticity to generate endogenous dispersion across firms in markups and pass-through elasticities. We test the model's predictions on a representative sample of French manufacturing firms over the period 2004-2014. We establish causality by exploiting a quasi-natural experiment induced by a policy change that affected firms' liquidity. Our results shed new light on the roots of rising markups and markup heterogeneity in recent years.

Key words: markups, financial constraints, intangibles, productivity, technological change
JEL codes: D22; D24; G32

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Carlo Altomente, Boccconi University. Domenico Favoino, Erasmus University. Monica Morlacco, University of Southern California. Tommaso Sonno, University of Bologna and Centre for Economic Performance, London School of Economics.

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# 1 Introduction

Business dynamism has remained surprisingly low over the last three decades, while corporate profits, market concentration and markups have all been rising. These trends have prompted a growing theoretical and empirical literature on the evolution of firm-level markups.[1] Economists have attributed at least part of these dynamics to the increasing importance of companies' intangible assets - such as software and IT systems - for growth and profitability. Since, as the argument goes, intangibles are scalable and exhibit synergies, firms that manage to adopt them gain a competitive advantage, breaking away from competition (Haskel and Westlake, 2018; Autor et al., 2020; Akcigit and Ates, 2019, 2020).[2]

Identifying the factors that determine intangible investment is thus essential in determining the root cause of increasing markups and understanding whether or not regulatory action is warranted. Are certain firms simply better than others at adopting intangibles, or do some frictions give these firms a competitive edge over their rivals? We tackle this question and investigate the role of financial frictions for intangible investment decisions, and ultimately for differences in markup behavior across firms.

We have elected to focus on such frictions because of the extensive literature in finance arguing that the increase in intangibles poses significant challenges for firm financing.[3] While tangible capital can be used as collateral, providing lenders with some protection against default, information problems, and lack of collateral value can hamper firms' ability to borrow in the case of intangibles, making them more vulnerable to financing constraints. Despite the critical role of financial frictions in shaping intangible investment decisions, the macroeconomic literature has largely overlooked their consequences for intangibles' and markups' dynamics.

This paper makes three related contributions. First, we develop a model with imperfect financial markets, firm heterogeneity, and variable demand elasticity to characterize the equilibrium relationship between heterogeneous financial constraints, intangible investment, and firm-level markups. Second, we test the model's prediction using a quasi-experimental variation in financial

[1] See, e.g. De Loecker and Eeckhout (2018); De Loecker et al. (2019); Gutiérrez and Philippon (2017); Syverson (2019); Barkai (2019); Akcigit and Ates (2020); Eggertsson et al. (2018). On criticisms of the evidence of rising markup trends on the grounds of measurement concerns, see Karabarbounis and Neiman (2019); Traina (2018).

[2] For empirical evidence linking intangibles to increasing concentration and markups, see Andrews et al. (2016); Calligaris et al. (2018); Bessen (2017); Crouzet and Eberly (2018); De Ridder (2019); Autor et al. (2020); Sandström (2020).

[3] See, e.g., Hall and Lerner (2010); Loumioti (2012); Mann (2018); Cecchetti and Schoenholtz (2018); Lim et al. (2020).

constraints across French firms. Specifically, we report new empirical evidence that a positive and arguably exogenous shock to liquidity leads to a significant increase in the amount of intangible assets held by firms. We then show that by increasing their intangibles, firms can charge significantly higher markups over marginal costs. Importantly, this latter effect is mediated by financial constraints: firms with ex-ante better access to finance can increase their markups by more following the liquidity shock, i.e., they have higher pass-through elasticity to markups. We conclude that financial factors are an essential and largely overlooked source of differences in markups and pass-through elasticity between firms. This is the paper's third and final contribution.

To consider how financial frictions are related to intangible investment and markups, we use balance-sheet data for a large sample of French manufacturing firms from 2004 to 2014, retrieved from the Bureau van Dijk's Amadeus database. A major advantage of our dataset is that it spans a period of time when France underwent a series of reforms to foster industrial competition and growth by improving firms' financing. We leverage on one such policy reform to establish our main causal results.

To guide the empirical analysis, we incorporate imperfect financial markets into a static partial equilibrium model of production with firm heterogeneity, intangible assets, and variable demand elasticity. In the model, companies' need for external capital arises when they want to invest in a modern *intangible* technology that features a high front-loaded fixed cost in exchange for a reduction in variable costs. Liquidity-constrained firms have access to banks to finance this investment, but they can only borrow if they pledge the required amount of collateral. Financial frictions result from two separate processes: an aggregate component, captured by a collateral constraint, and an idiosyncratic component, captured by the firm's heterogeneous borrowing cost. We refer to the latter as the firm's *financial capability*.[4,5]

Financial capability is a source of competitive advantage. Heterogeneity in the cost of borrowing induces dispersion in the shadow cost of intangible capital, affecting both the extensive and

[4]The collateral constraint reflects, for instance, bank policies or regulations common to all firms. Financial capability instead reflects all these factors affecting the cost of borrowing or borrowing opportunities of firms. These factors include heterogeneity in retained earnings, bank-firm relationships, asymmetric information, and moral hazard problems between entrepreneurs and investors (e.g., Hall and Lerner, 2010).

[5]In our theoretical model, financial capability is the only source of heterogeneity across firms. This assumption is made for analytical tractability and is without loss of generality. All the results would still hold in a more general model where firms are heterogeneous both in financial capability and production efficiency. In the empirical analysis, we show that our results are robust to controlling for measures of firm productive efficiency.

intensive margin of intangible investment. At the extensive margin, firms choose to adopt intangibles only if their financial capability is great enough. At the intensive margin, firms with greater financial capability choose to invest relatively more, become relatively more efficient, and charge higher markups. The source of markup variation in the model is the variable elasticity of demand: firms with lower marginal costs have lower demand elasticity and charge higher markups. Moreover, our demand-side assumptions imply that heterogeneity in financial capability further induces dispersion in the pass-through elasticity of marginal cost shocks into markups and prices.

We test the model's predictions causally by exploiting a quasi-natural experiment in France that limited the term on the credit firms could receive from their suppliers. In January 2009, a law introduced a cap of 60 days on the payment terms authorized in domestic transactions. This was a positive liquidity shock to suppliers whose repayment delays had previously exceeded 60 days (Beaumont and Lenoir, 2019). We retrieve information on individual firms' payment terms from our data; we link the model to the data considering the exogenous shock to liquidity for some firms as a shock to their financial capability.

Our first empirical result is a positive causal relationship between financial capability and intangible investment. We measure intangibles as total firm expenditure on fixed costs, which we obtain as net revenues minus operating profits.[6] We adopt a difference-in-differences identification strategy that exploits firms' cross-sectional variation in the distance from the 60-day threshold. Specifically, we test whether the intangible assets of firms that are further from the threshold (first difference) are greater after the change in policy than intangibles before the policy change (second difference).[7] The baseline specification implies that moving a firm from the 25th to the 75th percentile of the distribution of the net distance from the threshold leads to increased intangible expenditures by 4.4 percentage points following the liquidity shock.

Our second result is a positive causal relationship between intangibles and firm-level markups. We construct the markups using the cost-based approach of De Loecker and Warzynski (2012). To address common endogeneity concerns, we adopt an instrumental variable strategy instrumenting intangible investment with the exogenous liquidity shock of the reform, effectively using the

[6] In the empirical section, we discuss sensitivity analysis for this as well as for our markup measures.

[7] Importantly, in our baseline definition of the treatment group, we consider the entire network of input-output relationships and allow for the possibility that a firm is simultaneously affected by the policy shock positively (as a supplier) but also negatively (as a buyer).

results of the difference-in-differences analysis as our first stage estimation. We show a substantial causal relationship between intangible investment and firm-level markups. The results are economically significant: the baseline estimates imply that firms that increase their intangible holdings by 10% can increase their price-cost margins by more than 2 percentage points.

Our third and final result is that the effect of intangibles on markups is heterogeneous across firms. The more financially capable firms operate on a less elastic part of the demand function in the model, and they manage to pass a higher portion of the shock through to markups. Our identification strategy consists of augmenting the IV specification with an interaction term between the intangibles and a proxy for financial capacity. In line with the model's predictions, the markup pass-through of shocks to marginal costs driven by the shifts in intangibles is larger for the more financially capable firms.

We have conducted several exercises to gauge the robustness of these results and the identification strategy. First, we have replicated the principal difference-in-difference analysis taking other types of investment as the dependent variable, finding that intangibles are more sensitive to liquidity constraints than any other form of capital, in line with our prior. Next, we ran a battery of checks to rule out the possibility that markups may be affected by the liquidity shock via channels other than intangible investment, showing that the shock has no impact on such variables as employment, revenue productivity, and export behavior. This evidence is consistent with our claim that liquidity shocks have affected markups only through the intangibles channel; it also validates our instrumental variable strategy's exclusion restriction. Overall, our evidence appears to indicate that confounding factors play only a minor role in our context.

**Related Literature** Our work makes contact with several strands of the literature. First and foremost, this paper's analysis contributes to the literature emphasizing the role of financing constraints for innovation and development.[8] Our contribution to this literature is twofold: first, we produce direct evidence of a limiting effect of liquidity constraints on intangible investment. A large body of empirical work has shown that financial barriers directly affect firm-level R&D expenditures (Brown et al., 2012; Aghion et al., 2012; Hall et al., 2016); the existing evidence on

[8]E.g. Hall and Lerner (2010); Kerr and Nanda (2015); Hubbard (1998); Buera et al. (2011); Aghion et al. (2010); Manova (2012); Midrigan and Xu (2014); Chaney (2016); Gopinath et al. (2017).

intangible assets is rather limited instead. Our findings resonate with a macro-finance literature showing that firms who use intangible assets resort to less debt, a traditional form of financing for European firms (Bates et al., 2009; Rampini and Viswanathan, 2013; Döttling et al., 2019). Our second contribution is to relate heterogeneity in financial constraints with markups' dispersion across firms. The markup channel has been largely overlooked in the literature, which usually relies on theoretical frameworks where markups are exogenous.[9]

Secondly, our analysis speaks to the substantial literature relating markups and pass-through heterogeneity to firm characteristics.[10] While previous studies have focused on heterogeneity along the dimensions of productivity, size, and export status, this is the first to show, both theoretically and empirically, that financial factors are an important source of markups and pass-through heterogeneity.

Finally, this paper contributes to the extensive debate on industry concentration and markup dynamics in modern economies. Our evidence supports technology-based theories that relate the observed increase in markups to the rise of intangibles.[11] One common argument in this literature is that large markups and industry concentration stem from an efficient reallocation of market shares from low- to high-efficiency firms, i.e., efficiency gains in the economy as a whole (Autor et al., 2020). Our results, however, imply that insofar as firms' competitive advantage depends on financial frictions, the ensuing reallocation of market shares is not necessarily efficient. A second, related indication is that the rise of intangibles may have amplified the role of financial frictions for the aggregate economy. In turn, financial constraints may have contributed to the evolution of markups and profit inequality across firms.[12]

**Structure of the paper** The paper is structured as follows. Section 2 introduces our theoretical framework and sets out predictions. Section 3 describes the firm-level data and the main covari-

[9]Two exceptions are Peters and Schnitzer (2015) and Egger et al. (2018), who study the role of credit constraints in models with variable markups. In both of these papers, aggregate credit constraints affect productivity and markups by altering the overall extent of technology adoption and market entry. Unlike these papers, we introduce heterogeneity in credit constraints across firms and study the intensive margin response of investment and markups, showing that accounting for both the intensive and the extensive margin effects is the key to rationalizing the empirical evidence.

[10]De Loecker and Warzynski (2012); Edmond et al. (2015); Arkolakis et al. (2018); Peters (2020) among others, focus on markups heterogeneity while Berman et al. (2012); Amiti et al. (2014); Burstein and Gopinath (2014); Arkolakis and Morlacco (2017) focus on heterogeneous pass-through elasticities.

[11]See, e.g., Crouzet and Eberly (2018); De Ridder (2019); Sandström (2020)

[12]Studies that document the increase in dispersion in firms' profits and profitability include Furman and Orszag (2015); Andrews et al. (2016); Autor et al. (2020); De Loecker et al. (2019); Haskel and Westlake (2018).

ates. Our empirical strategy and main results are discussed in Section 4. Section 5 shows evidence on the heterogeneous effects of financial frictions on markups, and Section 6 explores alternative explanations for the results. Section 7 concludes.

# 2 Theoretical Framework

We employ a static partial equilibrium model with heterogeneous firms to investigate the equilibrium relationship between financial variables, intangible assets, and profitability. We build the most parsimonious model that allows us to address this question in the context of our data. The model is intended primarily for application to the manufacturing sector.

## 2.1 Environment

There are two types of agents: workers and firms. The representative worker derives utility from differentiated varieties of consumption of the final good and supplies labor to firms. Each variety of the final good is produced by a different firm. We use $i$ to index both firms and varieties.

**Demand** The focus on markup heterogeneity requires departing from demand systems that imply constant markups across firms, such as the constant elasticity of substitution (CES) case. Instead we posit a general homothetic demand system for differentiated goods that encompasses a number of prominent alternatives to CES, building on Arkolakis et al. (2018). The representative consumer's demand for variety $i$ when income is $Y$ and prices are $\{p_i\}_{i \in M}$, is

$$c_i \equiv C(p_i, P, Q) = QD\left(p_i/P\right), \tag{1}$$

where $D\left(y\right) \in \mathcal{C}^2(y)$ is a twice continuously differentiable function, with $D'_y < 0$. Firms take the aggregate demand shifters $Q(\boldsymbol{p}, Y)$ and $P(\boldsymbol{p}, Y)$ as given; they are jointly determined from standard utility maximization constraints.[13]

[13] The aggregate shifters $Q(\boldsymbol{p}, Y)$ and $P(\boldsymbol{p}, Y)$ solve the following system of equations:

$$\begin{aligned} \int_{\omega \in \Omega} \left[H\left(\tfrac{p_\omega}{P}\right)\right] d\omega &= 1 \\ \int_{\omega \in \Omega} p_\omega Q D\left(\tfrac{p_\omega}{P}\right) d\omega &= Y, \end{aligned}$$

with $H(\cdot)$ strictly increasing and concave.

We denote the elasticity of demand as $\varepsilon(y) = -\partial \ln D(y) / \partial \ln y$, where $y \equiv p/P$. The demand elasticity varies with the prices charged by different firms. We impose that $\varepsilon' > 0$, i.e. demand is more elastic for firms that charge higher relative prices, which implies that markups are greater for the more efficient firms. This condition, known as Marshall's (weak) second law of demand, is justified by a large empirical literature.[14]

**Firms and Technology** There is free entry into production, subject to an initial entry cost $f_e > 0$. Each producer $i$ has access to two production technologies: *(i)* a *traditional*, constant returns technology, with labor as the sole input; or *(ii)* a *modern* technology, which increases the fixed costs of production in exchange for a reduction in the variable cost (Hsieh and Rossi-Hansberg, 2019; De Ridder, 2019). We let $s_i \in [0, 1)$ denote the marginal cost reduction of firm $i$ associated with the modern technology. The firm can choose whether or not to adopt the modern technology (extensive margin), and how much of the modern technology to adopt by choosing the optimal level of $s_i \in [0, 1)$ (intensive margin). The greater the desired marginal cost reduction $s_i$, the higher the fixed costs paid. We denote by $f(s)$ the fixed cost function, such that $f' > 0$, $f'' > 0$ and $\lim_{s \to 1} f = \infty$. We interpret the modern technology as one that combines labor with some intangible asset that makes the firm more productive, so we will use the terms "intangible capital" and "fixed-cost technology" interchangeably. Regardless of which technology they ultimately adopt, firms can hire any desired amount of labor at a fixed unitary wage $w$, normalized to one.

The decision on which technology to adopt depends on the relative returns. The total cost function of firm $i$ can be written as:

$$TC(q_i) = \mathbb{I}_{S,i} \cdot [(1 - s_i)q_i + f(s_i)] + (1 - \mathbb{I}_{S,i}) \cdot q_i, \tag{2}$$

where $q_i$ is total output of firm $i$, and $\mathbb{I}_{S,i}$ is an indicator equal to 1 if the firm adopts the modern technology, i.e. if $s_i > 0$. Adopting the modern technology front-loads a significant fraction of the production expenses in the form of fixed costs, in exchange for lower unit costs in the production process. It follows that the shape of the fixed cost function $f(s)$, and the extent to which firms are constrained in accessing external finance, play a key role in the firm's choice of intangibles.

[14] See Melitz (2018) or Burstein and Gopinath (2014); Arkolakis and Morlacco (2017) for reviews of the empirical evidence.

## 2.2 Credit-constrained Producers

Firms that want to invest in the modern technology cannot pledge future revenues or retained earnings to pay the fixed costs. Their financing options are limited to an external banking sector, from which they can borrow if they post the required amount of collateral.

Consistent with extensive evidence in the financial literature, we assume that firms differ in their cost of raising external funds.[15] We let $\tau \in \mathbb{R}_+$ denote an inverse measure of the firm's cost of external finance, which we refer to as the firm's *financial capability*. We assume that the value of $\tau$ is exogenous and is drawn upon entry from a cumulative distribution function $G(\tau)$ with support over $[\underline{\tau}, \infty)$, with $\underline{\tau} > 0$.

To flexibly capture the role of $\tau$ for investment decisions, we assume that a firm whose financial capability is $\tau$ and intends to make an investment of size $f(s)$ needs to ask for a loan of size $g(s,\tau) = \left(1 + \frac{1}{\tau}\right) f(s)$. Only for the most financially capable firms ($\tau \to \infty$), will the size of the loan correspond to the size of the investment, i.e., $\lim_{\tau\to\infty} g(s,\tau) = f(s)$. For the others ($\tau < \infty$), the effective debt is higher than the amount of fixed costs they had to finance $g(s,\tau) > f(s)$. The wedge between $g(s,\tau)$ and $f(s)$ is decreasing in the firm's financial capability, which thus captures heterogeneity in the cost of borrowing or borrowing opportunities across firms, such as retained earnings, bank-firm relationships, and asymmetric information.

**Banks** Firms can pledge a fraction $\theta \in (0,1)$ of the initial entry cost $f_e$ as collateral.[16] The term $\theta$ is common across firms, and it captures (inversely) the tightness of the financial market. The lower $\theta$, the less collateral firms can pledge, the greater the repayment needed to induce banks to participate. Firms that pledge the required level of collateral have to repay $R(s,\tau)$ to banks. Repayment occurs with exogenous probability $\lambda \in [0,1]$ (as in Manova, 2012). With probability $(1-\lambda)$ the firm defaults, and the bank seizes the collateral $\theta f_e$. The bank's participation constraint is thus:

$$-g(s,\tau) + [\lambda R(s,\tau) + (1-\lambda)\theta f_e] \geq 0. \tag{3}$$

[15]See, e.g. Whited and Wu (2006); Hadlock and Pierce (2010); Cloyne et al. (2018); Ottonello and Winberry (2020). In particular, see Hall and Lerner (2010) for a review of the empirical evidence on the importance of heterogeneous constraints for the financing of intangibles.

[16]This assumption is standard in the literature of financial frictions. The main theoretical results would be unchanged if we assumed that the collateral requirement is revenue-(or quantity-)based instead.

Given perfect competition in banking, the participation constraint holds with equality for all banks. It follows that the payment $R(s,\tau)$ is determined by the firms so as to bring the financier to his/her participation constraint.

### 2.3 The Firm's Problem

We start by characterizing the equilibrium of an incumbent firm $i$ who has decided to adopt intangibles; subsequently, we return to the firm's technology adoption decision.[17]

A firm that invests in the modern technology chooses the price $p$ and the intangible investment $s$ that solve the following problem:

$$\max_{p,s} (p-1+s)q(p/P,Q) - [\lambda R(s,\tau) + (1-\lambda)\theta f_e],$$

$$\text{s.t. } q(p/P,Q) = QD\,(p/P) \tag{4}$$

$$(p-1+s)q(p/P,Q) \geq R(s,\tau) \tag{5}$$

$$-g(s,\tau) + [\lambda R(s,\tau) + (1-\lambda)\theta f_e] = 0. \tag{6}$$

where (4) is the demand function, (5) is the firm's liquidity constraint, which guarantees that profits after debt repayment are non-negative, and (6) is the bank's participation constraint.

We solve the problem by first considering instances when the liquidity constraint does not bind. Substituting (4) and the bank participation constraint (6) into the profit function, we obtain:

$$\max_{p,s} (p-1+s)QD\,(p/P) - g(s,\tau). \tag{7}$$

Note that firms that adopt the modern technology are heterogeneous both *ex-ante* and *ex-post*, owing to the effect of heterogeneous financial capability $\tau$ on the firm's effective cost of investment $g(s,\tau)$. Conversely, firms that decide not to adopt intangibles are ex-post homogeneous.

**Intangibles and Financial Frictions** Let $\rho(s) \equiv (\mu(s)-1)\,(1-s)QD\,(p(s)/P)$ denote a firm's variable profits expressed as a function of $s$. The first order condition associated with (7) governing

[17] Given the nature of our empirical exercise, we abstract from the decision to enter the production stage and consider the number of incumbent firms as exogenously given.

the optimal choice of intangibles by a firm with financial capability $\tau$ is:

$$\rho'(s) = \left(1 + \frac{1}{\tau}\right) f'(s), \tag{8}$$

where $f'(s)$ denotes the marginal increase in fixed cost associated with intangible investment of size $s$. Condition (8) states simply that the firm chooses the level of $s$ that sets the marginal variable profit equal to the marginal increase in financial liabilities. Ceteris paribus, firms with higher $\tau$ have a lower shadow cost of investment and optimally choose higher $s$. In Appendix C, we prove that equation (8) admits a unique solution of the form $s = s(\tau)$, with $s' > 0$. The latter can be synthesized as:

TESTABLE PREDICTION 1. *All else constant, firms with higher $\tau$ invest more in intangibles.*

**Markups and Intangibles** For a given level of intangibles $s$, the problem in (7) is isomorphic to that of an unconstrained firm producing with constant marginal cost equal to $1 - s$. The optimal price is obtained as a markup over marginal cost:

$$p = \mu \cdot (1 - s), \tag{9}$$

where $\mu = \mu(y)$, where $y \equiv p/P$ is the relative price. Let us denote by $\Gamma \equiv -\frac{d \ln \mu(y)}{d \ln y} = \Gamma(y) > 0$ the elasticity of the markup to $y$.[18] By log-differentiating equation (9) and rearranging, we can write markups as a function of the investment choice $s$ and the price index $P$ :

$$d \ln \mu(s) = \frac{\Gamma}{1+\Gamma}\left(\frac{s}{1-s} d \ln s + d \ln P\right). \tag{10}$$

Equation (10) shows that variation in the choice of intangible assets induces variation of markups across firms. The higher the choice of $s$, the higher the markup given $\frac{\Gamma}{1+\Gamma} > 0$. The second testable prediction follows immediately:

TESTABLE PREDICTION 2. *All else constant, firms that invest more in intangibles charge higher markups over marginal costs.*

[18]Our assumption on $D(\cdot)$ implies that $\Gamma \geq 0$. With CES demand, markups are constant and $\Gamma = 0$.

A corollary of testable predictions 1 and 2 is that dispersion in markups across firms is correlated to firms' heterogeneous financial capability through its effect on intangible investment.

**Pass-through Elasticities** We define the pass-through elasticity of markups as the percentage change in markups following a one percent shock to marginal costs, i.e. $\Phi(s) \equiv -\frac{d\ln\mu}{d\ln(1-s)}$. The elasticity $\Gamma$ is a key parameter governing the pass-through of marginal cost shocks to markups and prices. From equation (10), it is easy to see that holding aggregate prices fixed, the markup's pass-through elasticity is: $\Phi(s)|_{\Delta P=0} = \frac{\Gamma(s)}{1+\Gamma(s)} \in (0,1)$.[19]

To the extent that $\Gamma$ varies with $s$, our model predicts that different firms respond differently to a common marginal cost shock. In particular, we show in Appendix C that:

$$\frac{d\Phi(s)}{ds} > 0, \tag{11}$$

whenever $\Gamma'_y \leq 0$. The latter condition holds whenever the pass-through of shocks is larger for firms that charge lower prices; this condition is consistent with a good deal of empirical evidence on heterogeneous pass-through across firms (Berman et al., 2012; Amiti et al., 2014). The third implication of the model follows:

TESTABLE PREDICTION 3. *All else constant, the pass-through of a common marginal cost shock to markups is higher for firms with higher intangible asset levels.*

## 2.4 Selection into Investment

We conclude our description of the theoretical model with a discussion on the firm's extensive margin decision to invest in the modern technology. Let $\pi^R_M(\tau_i)$ denote ex-post profits from operating the modern technology in case of repayment, and $\pi_T$ expected profits from operating the traditional technology, where $\tau_i$ is the exogenous financial capability of firm $i$. The firm's ex-ante

[19] The pass-through of a shock to the marginal cost, taking general equilibrium effects into account, is given by

$$\Phi(s) \equiv -\frac{d\ln\mu}{d\ln(1-s)} = \frac{\Gamma(s)}{1+\Gamma(s)}\left(1 - \frac{d\ln P}{d\ln(1-s)}\right) \in (0,1),$$

and depends both on $\Gamma(s)$ and on the GE equilibrium changes in aggregate prices $P$ due to the shock.

profits are:

$$\pi(\tau_i) = \max \left\{ \underbrace{\pi_T}_{\text{Traditional technology}} \quad ; \quad \underbrace{\lambda \pi_M^R(\tau_i)}_{\text{Modern technology}} \right\}. \tag{12}$$

Since the traditional technology does not require financing ex-ante fixed costs, the profits $\pi_T$ do not depend on financial capability and are thus constant across firms. Because firms operating the traditional technology are ex-post homogeneous, and because there is free entry to production, the profits of firms in this sector, net of the fixed entry costs $f_e$, are always zero.[20] It follows that a firm will adopt the modern technology as long as $\pi_M^R(\tau_i) \geq 0$.

Therefore, the intangibles adoption decision is determined by the set of firms for which the liquidity constraint is binding. We infer the payment $R(s,\tau)$ from the bank's participation constraint and substitute it into (5) to write:

$$\rho(s(\tau)) - \frac{1}{\lambda}\left[\left(1 + \frac{1}{\tau}\right) f(s(\tau))\right] = -\left(\frac{1-\lambda}{\lambda}\right)\theta f_E, \tag{13}$$

where $\rho(\tau)$ denotes a firm's net revenues expressed as a function of $\tau$. The left-hand side of (13) is an increasing function of $\tau$, and is negative for $\tau \to 0$ given $\lambda \in (0,1)$. It follows that the solution to equation (13) is a cutoff rule, whereby only the more financially efficient firms invest in the intangible technology. Linking back to this paper's main theme, this result implies that financial capability can provide firms with an edge over the competition by providing access to a cost-reducing technology that allows them to produce more efficiently and charge higher markups.

The entry cutoff depends on the severity of aggregate financial market imperfections, i.e. $\tau^* = \tau^*(\lambda, \theta)$. It is easy to show that:

$$\tfrac{\partial \tau^*}{\partial \theta} > 0 \quad \& \quad \tfrac{\partial \tau^*}{\partial \lambda} < 0 \ \cdot \tag{14}$$

Low values of either $\theta$ or $\lambda$ - corresponding to tighter financial markets - raise the entry barriers and tighten the entry cutoff. It follows that the effect of aggregate financial shocks on the overall level of investment and aggregate markups is, in principle, ambiguous. The intuition is that tighter collateral constraints (lower $\theta$) tighten the entry cutoff into the "modern" sector, leading to higher

[20] The value of $\pi_T$ can be found by solving a standard profit-maximization problem, namely $\max_p\,(p-1)QD\,(p/P)$, which will yield as optimal solution a price equal to the markup, namely $p = \mu(y)$, where $\mu(y) \equiv \varepsilon(y)/(\varepsilon(y)-1)$ and $y = p/P$.

investment and markups of firms already investing in the modern technology. However, as more firms then operate the traditional technology, the measure of firms with low levels of investment and markups increases. Overall, the aggregate effect of financial frictions depends on whether the intensive or extensive margin prevails. This remains ultimately an empirical question.

### 2.5 Discussion

Before turning to the data to test the model's predictions, let us discuss some of the assumptions. First, in our model, financial capability is the only source of heterogeneity across firms. In reality, of course, the returns to intangible investment may be heterogeneous across firms: younger firms may benefit more from intangibles than older firms; similarly, larger and more productive firms may be better able to manage intangibles, thus getting a higher return on the investment.

It is straightforward to extend the model to include multiple heterogeneity sources, most notably differences in production efficiency. All the results would hold even in this more general model, in a conditional sense. In the empirical analysis, we show that our results are broadly robust to controlling for several firm-level variables, including age and measures of revenue productivity.

A second assumption that needs critical appraisal is that differences in financial capability across firms are exogenously given in our static framework. A firm's financial capacity, however, is inherently dynamic, capturing the endogenous shadow cost of external funds to different firms (Midrigan and Xu, 2014). Our exogeneity assumption allows us to analytically isolate the role of heterogeneous financial frictions on markups, dramatically simplifying the exposition. Here, in any case, this assumption seems nevertheless justified by reliance in our empirical analysis on a quasi-experimental setup that yields exogenous variation in financial capability across firms. This enables us to test the model predictions consistently.

Finally, our model features a single sector in which an investment in traditional and modern technology can be undertaken. However, it is widely documented that industries differ in external capital requirements and the degree of asset collateralizability (Beck, 2002; Svaleryd and Vlachos, 2005; Manova, 2012). Sectoral heterogeneity may also affect the shape of the fixed-cost technology and the elasticity of marginal costs to intangible investment. In the empirical analysis, we allow for all these dimensions of heterogeneity by including four-digit sector fixed effects in all specifications, interacted with year fixed effects to capture demand shocks. All our results thus need to be interpreted as average effects.

# 3 The Data

The empirical analysis requires three key elements: a measure of intangible assets at the firm-level, a measure of firm-level markups, and a proxy for shocks to financial capability. We now discuss each of these elements, preceded by a discussion of the data and the sample construction.

## 3.1 Data and Variable Definitions

We take our panel of French manufacturing firms, 2004-2014, from the Orbis database provided by Bureau van Dijk. The Orbis database includes a wide array of balance sheet items, including profit accounts and financial variables.[21] We classify a firm as a manufacturing firm if it reports manufacturing as its primary activity and exclude all other firms.

**Sample Definition** We retain all firms for which we observe the required information to compute markups and intangible investment, i.e., firms with no missing values for sales, profits, employment, output, capital stock, and materials. We restrict the analysis to those firms that report the number of employees for more than 50% of the years in the sample, ending up with about 38,000 unique firms observed over time. Our final dataset is representative of the official size distribution of French firms within each two-digit industry.[22]

We work with three different samples. Our baseline sample retains all firms that enter before 2005 and exit after 2010.[23] This sample selection guarantees that any given firm appears both before and after the policy shock in 2008/09, mitigating concerns about changing sample composition. We then replicate our main results on a fully balanced sample, which only keeps those firms that are *always* present over the entire sample period, and on the original, unbalanced sample.

[21] Gopinath et al. (2017) have used similar Orbis data for Spain to study the effect of size-dependent financial frictions for aggregate productivity.

[22] To ensure representativeness, we construct weights based on firm total employment, building on the official size distribution of firms provided by the Eurostat-Structural Business Statistics. Weights are applied at the size class-industry-year level.

[23] Adjusting the initial and final years at the margin does not affect the results significantly.

Table 1: Summary Statistics

| | Obs. | Mean | St. Dev. | P25 | Median | P75 |
|---|---|---|---|---|---|---|
| *Intangibles* | | | | | | |
| Fixed Cost | 216,555 | 3,440,672 | 52,031,652 | 104,331 | 369,467 | 1,426,976 |
| *Markups* | | | | | | |
| Markup (Baseline) | 216,555 | 1.40 | 0.27 | 1.22 | 1.34 | 1.52 |
| Markup (Not Parametric) | 216,555 | 1.08 | 0.19 | 0.96 | 1.04 | 1.16 |
| *Covariates* | | | | | | |
| Sales | 216,555 | 14,229,231 | 241,813,376 | 482,632 | 1,474,800 | 5,465,300 |
| Current Liabilities | 216,555 | 4,391,706 | 63,883,948 | 123,000 | 394,052 | 1,506,435 |
| Loans | 216,555 | 465,825 | 5,394,619 | 0 | 11,499 | 89,399 |
| Cash Flows | 216,555 | 681,213 | 10,311,045 | 18,463 | 70,116 | 265,000 |
| Tangible Assets | 158,567 | 1,810,789 | 15,743,139 | 29,300 | 109,955 | 505,391 |

*Notes:* All nominal variables are deflated and denominated in 2010 Euros. Statistics are averaged over all years in the sample.

**Variable Construction** In our model, intangible assets are inputs that cause a shift from marginal to fixed costs. We thus measure intangibles as total firm expenditure on fixed costs, which we construct as net revenues minus operating profits, both of which are available from income statements.[24] The results are fully robust to an alternative measure of fixed cost rates, namely as the difference between the firm's marginal and average profitability, as in De Ridder (2019).

We build measures of firm-level markups following the "cost-based" approach of De Loecker and Warzynski (2012), which we adapt to our setup. Specifically, price-cost margins are inferred from the gap between output elasticity and the revenue share of variable inputs, measured by the cost of goods sold (henceforth COGS). Consistent with the theoretical model, we allow a firm's intangible investment to affect measured productivity, and in turn markups, at the firm level. In section B of the Appendix, we provide complete details on the estimation of the output elasticities and markups. We will show results using both this markup measure and an alternative "non-parametric" measure obtained by proxying the output elasticities with the average input cost share at the four-digit industry-year level.

## 3.2 Summary Statistics and Preliminary Evidence

Table 1 presents summary statistics for several key variables in our main sample. All the variables are deflated and expressed in 2010 euros, using industry-wide deflators drawn from the STAN Industrial Database. As is to be expected for firm-level data, the dispersion of all these variables

[24]Expenditures on intangibles are generally booked under *Selling, General and Administrative Expenses* (SG&A) in balance-sheet data that follow the U.S. GAAP accounting standards, such as Compustat (Gutiérrez and Philippon, 2017; De Loecker et al., 2019). In Orbis, however, the SG&A balance sheet item is not reported, as balance sheets are classified under the International Financial Reporting Standards (IFRS).

is substantial. Firms in the third quartile on average have around 10 times the sales and 14 times the fixed-cost expenditures as firms in the first quartile; they have substantially larger financial liabilities and charge a 25% higher markup over marginal costs. These data features are congruent with our theoretical model, where firms are (ex-post) heterogeneous in many dimensions.

Tables 2 and 3 show that the above dimensions of heterogeneity are meaningfully related to each other. Table 2 shows simple correlations, based on OLS regressions, of firm-level fixed-cost expenditures with measures of financial position, which include current liabilities, bank loans, cash flow and tangible assets, a proxy of the firm's ability to pledge collateral assets against external debt. All regressions include four-digit industry-year fixed effects. Columns (1)-(3) report correlations based on regressions that compare expenditures on fixed costs across firms. The results show that the firms that spend more on fixed costs have, on average, more current liabilities, more loans and higher collateral, indicating that they rely relatively more on external finance. Moreover, these firms are also more liquid, as is shown by the positive and significant coefficient for cash flows in column (3). The results are qualitatively similar when we include firm fixed effects and compare variables within-firm over time (columns (4)-(6)). The evidence in Table 2 is consistent with the assumption that expenditure on intangibles depends in important ways on the external financial sector.

Table 3 relates firm-level markups to fixed cost expenditures. The dependent variable in columns

Table 2: Fixed Costs and Financial Variables

| | Dependent Variable: ln $\text{Intan}_{it}$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Current $\text{Liabilities}_{it}$ | 0.847*** | | | | 0.186*** | | | |
| | (0.00447) | | | | (0.00766) | | | |
| $\text{Loans}_{it}$ | | 0.117*** | | | | 0.00539*** | | |
| | | (0.00172) | | | | (0.000356) | | |
| Cash $\text{Flows}_{it}$ | | | 0.536*** | | | | 0.0373*** | |
| | | | (0.00841) | | | | (0.00217) | |
| Tangible $\text{Assets}_{it}$ | | | | 0.462*** | | | | 0.0423*** |
| | | | | (0.00719) | | | | (0.00213) |
| Obs. | 216,293 | 216,245 | 193,042 | 158,213 | 216,293 | 216,245 | 193,007 | 158,209 |
| $R^2$ | 0.862 | 0.496 | 0.660 | 0.681 | 0.975 | 0.974 | 0.975 | 0.980 |
| Year $\times$ Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | No | No | No | No | Yes | Yes | Yes | Yes |

*Notes:* OLS estimations. Dependent variable: *ln* $Intan_{it}$ indicates (the log of 1+) firm-level intangible assets, measured as total firm expenditure on fixed costs. *ln Current* $Liabilities_{it}$, *ln* $Loans_{it}$, and *ln* $Cash_{it}$ are (the log of 1+) firm-level financial variables. All variables are deflated and expressed in 2010 Euros. All specifications include Year$\times$Industry fixed effects, columns (4)-(6) include firm fixed effects. Standard errors are in parentheses, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$.

Table 3: Intangibles and Markup

| Dependent Variable: | $\ln \mu_{it}$ (Baseline) | | $\ln \mu_{it}$ (NP) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\ln$ Intan$_{it}$ | 0.0121*** | 0.0685*** | 0.00953*** | 0.0594*** |
| | (0.000660) | (0.00127) | (0.000601) | (0.00115) |
| Obs. | 216,305 | 216,305 | 216,305 | 216,305 |
| $R^2$ | 0.207 | 0.797 | 0.073 | 0.765 |
| Year $\times$ Industry FE | Yes | Yes | Yes | Yes |
| Firm FE | No | Yes | No | Yes |

*Notes:* OLS estimations. Dependent variables: columns (1)-(2), *ln* $\mu_{it}$ *(Baseline)* indicates firm-level markups following De Loecker and Warzynski (2012); columns (3)-(4), *ln* $\mu_{it}$ *(NP)* indicates a non-parametric markup measure (obtained by proxying the output elasticities by the average input cost share at the industry-year level). *ln Intan*$_{it}$ indicates (the log of 1+) firm-level intangible assets, measured as total firm expenditure on fixed costs. All variables are deflated and expressed in 2010 Euros. Specifications (1) and (3) include Year$\times$Industry fixed effects, columns (2) and (4) include firm fixed effects. Standard errors are in parentheses and clustered at the firm level, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$.

(1) and (2) is the log of firm-level "cost-based" markups. Columns (3) and (4) take the log of the "non-parametric" markups. Columns (1) and (3) control for industry-year fixed effects, columns (2) and (4) use firm-level fixed effects. Firms that spend more on fixed costs turn out to charge higher markups on average.

The evidence in Tables 2 and 3 provides preliminary support to the model's predictions. However, an obvious problem with OLS regressions is that if the explanatory variables are correlated with the error term, they could lead to biased estimates of the coefficients. An example of such correlation is when firms respond optimally to positive demand shocks by investing more in cost-reducing technologies. The fact that in both tables, correlations differ substantially in the between and within specification suggests that our OLS estimates may indeed suffer from an omitted variable problem. In the next section, we develop an empirical strategy to deal with this concern.

# 4 Empirical Results

We identify the causal relationship between financial capability, intangibles, and markups, by exploiting a quasi-natural experiment, namely, a French policy measure that affected firm liquidity. After describing the policy shock, we discuss our identification strategy and then present the main empirical results, together with a battery of robustness and sensitivity checks.

### 4.1 Quasi-Experimental Setting

In August 2008, the French government approved a reform setting a cap on the payment terms authorized in transactions under the French trade code. The policy - sent into force on January 1st, 2009 - was part of a broader reform to modernize the French economy.[25] It prohibited French firms from accepting contractual payment terms exceeding sixty days after receipt of the invoice. Enforcement was strict and efficient throughout France, as it was managed by the seven regional Directorates of the Ministry of the Economy.

Following Beaumont and Lenoir (2019), we proxy the average time to *receive* payments for firm $i$ in year $t$ as the number of days of sales outstanding (DSO, henceforth), which we construct as the ratio of accounts receivable over sales, multiplied by 365:

$$\text{DSO}_{it} = \frac{\text{Accounts receivable}_{it}}{\text{Sales}_{it}} \times 365. \tag{15}$$

Intuitively, accounts receivable over sales represent the fraction of sales the company is still owed at the end of a fiscal year. Multiplying this ratio by 365 gives a daily rate. Similarly, we proxy the average time to *deliver* payments by firm $i$ in year $t$ as the number of days of payables outstanding (DPO, henceforth), which we construct as

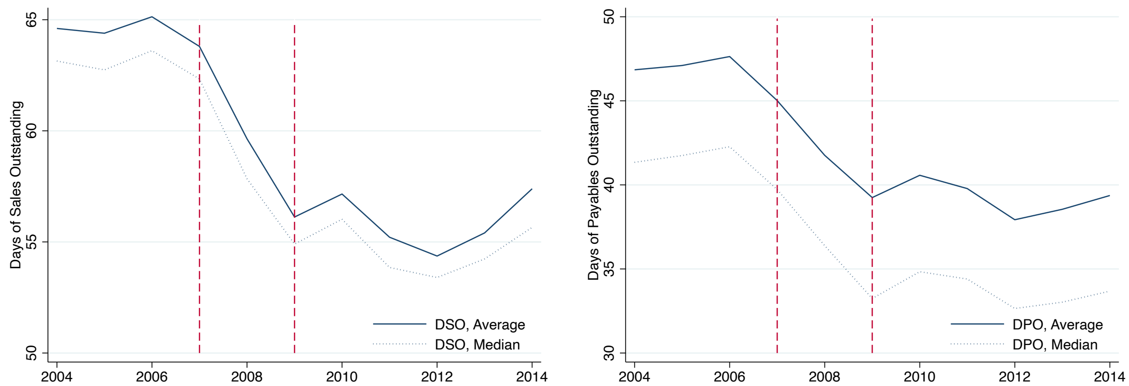
$$\text{DPO}_{it} = \frac{\text{Accounts payable}_{it}}{\text{Sales}_{it}} \times 365. \tag{16}$$

The average DSO before 2007 was 65.4 days for firms in our balanced sample, with a standard deviation of 43 days. The average DPO was substantially lower, at about 45 days, with a standard deviation of 30 days.

Figure 1 visually displays the impact of the policy: it shows the evolution of both mean and median DSO of firms in our baseline sample between 2004 and 2014. There is a clear drop in payment terms for the average firm, from around 65 days in 2007 to 57 in 2009 (left panel). The right panel shows DPO: the drop between 2007 and 2009, albeit smaller than that of DSO, is sharp. Like Beaumont and Lenoir (2019), we find evidence that the policy was anticipated by firms, as payment periods started to decline in 2007, a year before the law was enacted. We take this anticipation effect into account in the design of our identification strategy.

[25] Beaumont and Lenoir (2019) leverage the same policy reform to investigate the effect of liquidity constraints on investment in customer base and exports. We refer to their paper for a thorough description of the institutional context.

Figure 1: Evolution of DSO and DPO, 2004-2014




**a)** *DSO* **b)** *DPO*

*Notes:* Figures 2a and 2b show the evolution of both the average and median days of sales outstanding of firms (DSO) and of days of payables outstanding (DPO), respectively, between 2004 and 2014 in our baseline sample.

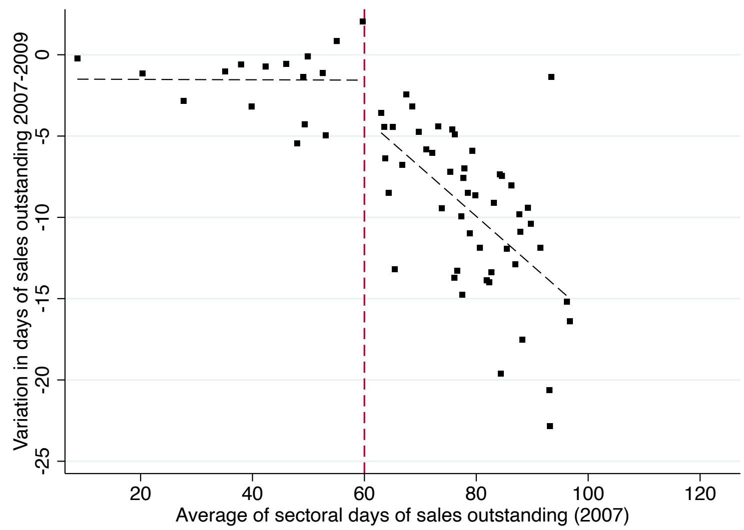
Figure 2 shows the shock to DSO across different firms. The x-axis displays percentiles of the industry average DSO in 2007. The y-axis gives the mean change in DSO between 2007 and 2009 (the year of implementation) for each percentile. The sharp kink suggests that industries where payment periods were longer than 60 days in 2007 experienced a much more significant DSO drop than other industries. We conclude that our DSO measure effectively picks up the effect of the 60-day rule on the variation in payment periods. Figure A1 in the Appendix shows the placebo exercise of considering changes in DSO between any two years before the policy shock, i.e., between 2004 and 2006. Before 2007, there is no significant correlation between the initial level of DSO and subsequent changes. This figure provides additional support to the thesis that DSO changes between 2007 and 2009 reflect the impact of the new policy.[26]

## 4.2 Intangibles and Liquidity

We exploit the policy shock to firms' liquidity to test the first theoretical prediction causally, namely that more financially capable firms will invest more in intangibles. In the model, financial capability is an inverse measure of the effective cost of external finance. We posit that firms benefiting from the shock see an increase in financial capacity: a firm with higher liquidity can more easily meet its short-term obligations and more likely obtain bank financing for intangible invest-

[26]Figures 2 and A1 replicate the figures in Beaumont and Lenoir (2019), who work with a different yet similarly representative sample of French firms, and focus on both manufacturing and wholesale trade.

Figure 2: Impact of the policy on payment days, 2007-2009




*Notes:* This graph displays the difference in days of sales outstanding between 2007 and 2009 as a function of the average DSO in 2007 for each NACE-4 digit industry. DSO is computed as the firm-level ratio of accounts receivable over sales multiplied by 365. The data set is split in 100 percentiles along the x-axis; the ordinate axis represents the average value of the y variable in each percentile.

ment. Alternatively, the additional liquidity can finance a fraction of the fixed-cost investment.

We explore the relationship between financial capability and intangibles using a generalized OLS difference-in-differences (DID) specification that examines whether the intangible assets of treated firms (first difference) are higher after the policy change than intangibles before the change (second difference). We consider three distinct definitions of the treatment group. The first and simplest considers a firm $i$ as treated if its average DSO before the policy shock was above the 60-day threshold, i.e.:

$$T_{1,i} = \mathbb{1} \cdot (DSO_{pre,i} > 60), \tag{17}$$

where $DSO_{pre,i}$ is the average DSO of firm $i$ between 2004 and 2007. Some 55% of sample firms are treated by this definition, and thus benefit from improved liquidity after the policy change.

The second definition considers both accounts receivable and accounts payable by allowing for the possibility that a firm gets both a positive shock vis-á-vis customers (via the reduction in average DSO) and a negative shock vis-á-vis suppliers (via the corresponding reduction in DPO). This second approach defines as treated only firms that have positive *net effect*, removing from the first set of treated firms those whose net financial position has worsened, i.e.:

$$T_{2,i} = \mathbb{1} \cdot (DSO_{pre,i} - DPO_{pre,i} > 0). \tag{18}$$

Around 50% of the sample firms experience a net financial improvement by this definition.

The third and preferred definition considers the net treatment effect as a continuous variable, acknowledging the possibility of a more significant liquidity shock for the firms that were further away from the threshold before the policy. The treatment intensity of firm $i$ is defined as:

$$T_{3,i} = \max\{0, \ln(DSO_{pre,i} - DPO_{pre,i})\}. \tag{19}$$

**Difference-in-differences** We estimate the following equation:

$$\ln(\text{Intan})_{it} = \alpha + \beta \cdot Post_t \times T_{j,it} + Post_t \times X_i'\gamma + X_{i(t)}'\lambda + \delta_{st} + \epsilon_{it}, \quad j = 1, 2, 3. \tag{20}$$

The dependent variable is the log of intangible expenditures of firm $i$ at time $t$. The second term on the right-hand side is the DID term of interest: an interaction of the treatment variable ($T_{j,it}$, $j \in \{1, 2, 3\}$) with an indicator for the post-change period. The third term is an interaction of the post-change indicator with time-invariant firm characteristics, namely initial year (2004) sales, cash flows, loans, and liabilities. This term allows for the possibility that the relationship between intangibles and these characteristics may differ in the post-change period; it serves as control in some specifications. The same firm-level controls enter other specifications, either as time-invariant firm-specific characteristics or variable over time. The fourth term in equation (20) describes these specifications. Finally, the term $\delta_{st}$ represents industry-time fixed effects, capturing the impact of any industry-level trend, notably demand shocks. Note that the set of controls allows for a liquidity shock having different effects depending on the firm's asset structure. This is important, as it allows comparing the outcome of observationally similar firms over time, thus isolating the differential impact of the policy change.

The results are reported in Table 4 with robust standard errors clustered by firm. Columns (1)-(3), (4)-(6), and (7)-(9) show the results using definition 1, 2, and 3. They differ in the set of controls, which are indicated in the bottom row. Our preferred estimates include firm-specific

Table 4: Financial Capability and Intangibles

| | Dependent Variable: ln $\text{Intan}_{it}$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $T_{1,it} \times \text{Post}_t$ | 0.034* | 0.043** | 0.019 | | | | | | |
| | (0.017) | (0.018) | (0.016) | | | | | | |
| $T_{2,it} \times \text{Post}_t$ | | | | 0.034** | 0.039** | 0.027* | | | |
| | | | | (0.017) | (0.017) | (0.015) | | | |
| $T_{3,it} \times \text{Post}_t$ | | | | | | | 0.013*** | 0.013*** | 0.009** |
| | | | | | | | (0.004) | (0.004) | (0.004) |
| Obs. | 208,956 | 208,956 | 192,895 | 208,956 | 208,956 | 192,895 | 208,956 | 208,956 | 192,895 |
| $R^2$ | 0.914 | 0.914 | 0.943 | 0.914 | 0.914 | 0.943 | 0.914 | 0.914 | 0.943 |
| Fixed Effect | Industry $\times$ Year | | | | | | | | |
| Controls | $X_i$ | $Post_t \times X_i$ | $X_{it}$ | $X_i$ | $Post_t \times X_i$ | $X_{it}$ | $X_i$ | $Post_t \times X_i$ | $X_{it}$ |

*Notes:* The table shows DID coefficients obtained by running OLS on equation (20). Dependent variable: *ln Intan*$_{it}$ indicates (the log of 1+) firm-level intangible assets, measured as total firm expenditure on fixed costs. $T_{1,it}$ is a dummy = 1 if the firm-level average DSO before the policy shock was above the 60-day threshold. $T_{2,it}$ is a dummy = 1 if the firm has a positive *net treatment*, thus excluding from the first set of treated firms those whose net financial position has worsened after the policy shock. $T_{3,it}$ is the (log of the) difference between the pre-policy shock average DSO and DPO, replaced with zero when negative. $Post_t$ is a dummy = 1 after the implementation of the policy, namely after 2009 (included). All variables are deflated and expressed in 2010 Euros. All specifications include Year×Industry fixed effects. The set of controls includes firm sales, cash flows, loans and liabilities. These can be time invariant (measured in 2004), $X_i$, as in columns (1), (4), and (6), interacted with $Post_t$, as in columns (2), (5), and (7), or simultaneous, $X_{it}$, as columns (3), (6), and (9). Standard errors are in parentheses and clustered at the firm level, $^*$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$.

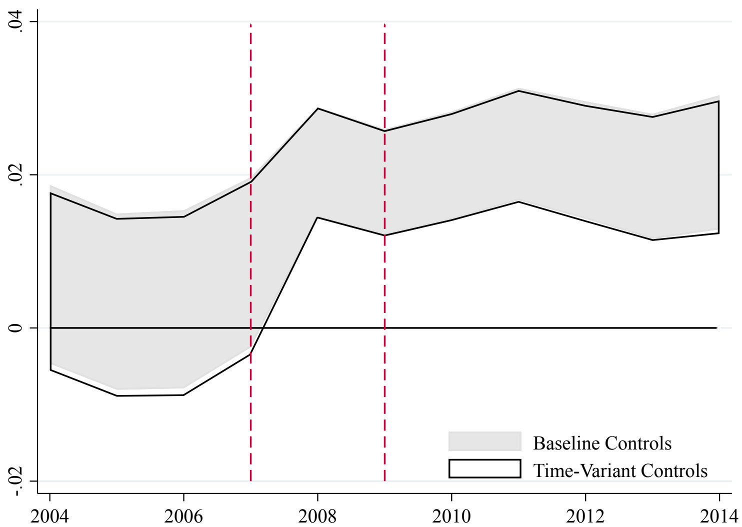
time-invariant controls and are reported in columns (1), (4), and (7). Our preferred specification is in column 7.

The estimates of the DID coefficient of interest are generally positive and statistically significant, indicating that the liquidity shock induced by the policy reform did produce higher intangible investment by the treated firms. Moving across the columns from left to right shows that the estimate of the DID coefficient is largely robust to different sets of controls, and remains statistically significant at conventional levels. The effects estimated are also economically significant. The coefficient in column 7 indicates that compared to a firm in the 25th percentile of the observed distribution of $T_{3,it}$ ($T_{3,it}$=0), a firm in the 75th percentile ($T_{3,it}$=3.41) increases its expenditure in intangibles by 4.4 (= 0.013 x 3.41) percentage points following the policy change.

**Robustness** For the increase in intangibles to be attributable to the liquidity shock, the distance from the 60-day threshold should be correlated with intangible expenditures only after the shock, not before. In order to verify whether treated firms spend significantly more on intangibles in the years before 2007, we consider the following specification:

$$\ln(\text{Intan})_{it} = \sum_{j=2004}^{2014} \pi_j \cdot T_{3,ij} + Post_t \times X_i'\gamma + X_{i(t)}'\lambda + \delta_{st} + \alpha + \epsilon_{it}, \quad (21)$$

Figure 3: Financial Capability and Intangibles - Robustness




*Notes:* The graph displays the coefficients $\pi_j$, with 95% confidence intervals, obtained from estimating equation (21) using OLS.

where the $Post_t$ indicator in equation (20) is replaced with a vector of interactions of the treatment indicator with a set of time dummies $\pi_j,\ j \in [2004, 2014]$ that take the value of one if $t = j$.

Figure 3 displays the 95% confidence areas for the coefficients $\pi_j$, obtained by running OLS on equation (21). We take $T_{3,it}$ as the baseline definition of the treatment variable, and we consider both a specification with only time-invariant controls $X_i$, and one in which the time-invariant controls are interacted with the post-change dummy.

The area shows the average differential effect of a one percent increase in the treatment variable $T_3$ on the treated firms' intangible expenditures. The effect is not significantly different from zero before 2007; it becomes a positive and significant one between 2007 and 2009, and it stabilizes after 2009. The result is fully robust to the different timing of firm-level controls.

Figure A2 in the Appendix compares the average treatment effects using the continuous and the dummy treatment definition. The effects are magnified in the latter case but are nevertheless robust to the treatment group's different definitions.

### 4.3 Markups, Intangibles and Financial Frictions

Having established the link between financial capability and intangibles, we now investigate the relationship between intangibles and markups. The second prediction of the model is that firms spending more on intangibles will charge higher markups over marginal costs. In the model, the firms that hold more intangible assets are those with greater financial capability. Therefore, the second prediction essentially links heterogeneous financial capacity to heterogeneous markup behavior through the intangible investment channel.

Table 3 provides some preliminary evidence for the prediction that intangibles and markups are positively related. However, as noted above, OLS estimates may be biased by unobserved shocks, such as demand shifters, correlated with the explanatory variables. Accordingly, we develop an instrumental variable strategy taking account of such endogeneity concerns while remaining consistent with the model's predicted behavior. Specifically, we use the policy shock as an instrument for intangible expenditure, which we then relate to firm-level markups in a second stage to draw causal inference. We consider the following specification:

$$\ln \mu_{it} = \alpha + \beta \ln(\text{Intan})_{it} + Post_t \times X_i' \gamma + X_{i(t)}' \lambda + \delta_{st} + \alpha + \epsilon_{it}, \tag{22}$$

where $\ln \mu_{it}$ denotes the log markup of firm $i$ at time $t$, and the remaining terms are as above. We run 2SLS regressions on (22), instrumenting intangibles with the DID setup described above.[27]

The results are reported in Table 5 with robust standard errors clustered by firm. The estimates of $\beta$ are positive and statistically significant in all specifications, indicating that firms that spend more on intangibles charge significantly higher markups. The results from our preferred specification in column 3 suggest that after a 10% increase in intangibles, a firm's price-cost margin widens by more than two percentage points.

The estimate for $\beta$ is broadly robust to different definitions of the treatment group. The IV regression seems correctly specified, given the high values of both the F-statistic on the excluded instruments and the p-value of the Hansen J-test of overidentification. Note that the coefficients on intangibles in Table 5 are substantially higher than those obtained in equivalent OLS regressions in Table 3, indicating that the OLS estimates are indeed negatively biased.

**Sensitivity Analysis** Table 6 shows a full battery of robustness checks on the baseline estimates reported in Table 5. For each of the three treatment indicators, we report the main IV estimate

[27] As a result, our first stage is a regression of $\ln \text{Intan}_{\text{it}}$ on three variables: the firm-level treatment, the dummy *Post*, and its interaction with the treatment.

Table 5: Markups, Intangibles and Financial Frictions

| | Dependent Variable: ln $\mu_{it}$ (Baseline) | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| ln Intan$_{it}$ [T$_{1,it}\times$Post$_t$] | 0.145*** | | |
| | (0.027) | | |
| ln Intan$_{it}$ [T$_{2,it}\times$Post$_t$] | | 0.196*** | |
| | | (0.035) | |
| ln Intan$_{it}$ [T$_{3,it}\times$Post$_t$] | | | 0.198*** |
| | | | (0.032) |
| Obs. | 208,956 | 208,956 | 208,956 |
| Industry $\times$ Year FE | Yes | Yes | Yes |
| Controls | $X_i$ | $X_i$ | $X_i$ |
| F-Stat | 25.61 | 17.16 | 22.63 |
| Hansen J | 0.68 | 0.28 | 0.39 |

*Notes:* The table shows the IV coefficients obtained by running 2SLS on equation (22). Dependent variable: *ln $\mu_{it}$ (Baseline)* indicates firm-level markups following De Loecker and Warzynski (2012). Different rows correspond to different definitions of the treatment group in the first stage. *ln Intan$_{it}$* indicates (the log of 1+) firm-level intangible assets, measured as total firm expenditure on fixed costs. We instrument it with the interaction of three different treatments with a post-change in policy variable. In column (1), the treatment $T_{1,it}$ is a dummy = 1 if the firm-level average DSO before the policy shock was above the 60-day threshold. In column (2), the treatment $T_{2,it}$ is a dummy = 1 if the firm has a positive net treatment, thus excluding from the first set of treated firms those whose net financial position has worsened after the policy shock. In column (3), the treatment is $T_{3,it}$, namely the (log of the) difference between the pre-policy shock average DSO and DPO, replaced with zero when negative. *Post$_t$* is a dummy = 1 after the implementation of the policy, namely after 2009 (included). All specifications include Year$\times$Industry fixed effects. The set of time invariant controls $X_i$ (measured in 2004) includes firm sales, cash flows, loans and liabilities. Kleibergen-Paap Wald F and Hansen J statistics are reported at the bottom of the table. Standard errors are in parentheses and clustered at the firm level, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$.

when the main specification in equation (22) is altered. In particular, the following changes are made: 1. using time-varying firm-level controls, i.e. our pre-period controls interacted with a dummy equal to one after 2008; 2. using simultaneous time-varying firm-level controls; 3. restricting the set of firm-specific controls to pre-period deflated sales; 4. performing the analysis on a fully balanced sample of firms over the entire period; 5. performing the analysis on the original unbalanced sample; 6. using a non-parametric measure of markups, the output elasticities being proxied by the average cost share of COGS at the four-digit industry-year level; 7. excluding the years from 2007 to 2009, to wipe out possible effects induced by the financial crisis; 8. including industry*year*region fixed effects, to control for demand shocks at the industry-region level; 9. adding controls for firm-level production efficiency, measured as value added per employee.[28,29]

[28] As discussed in Section 2.5, in our model financial capability is the only source of heterogeneity across firms, although extending the model to include heterogeneous production efficiency is straightforward and would produce entirely similar theoretical results. We control here for firm-specific labor productivity. We can also recover firm-specific TFP measures from the same production function estimation procedure that we use to construct firm-level markups, as discussed in Appendix B. The results would not change.

[29] The results obtained when using an alternative measure of intangibles constructed as the difference between the firm's marginal and average profitability as in De Ridder (2019) are almost identical, and are thus omitted. These results

Table 6: Robustness Checks

| | | Coefficient | St. Error | Obs. | Hansen J | F-stat |
|---|---|---|---|---|---|---|
| $T_{1,it}$ | Pre-period controls and their interactions with Post | 0.152*** | (0.025) | 208,956 | 0.61 | 28.64 |
| | Simultaneous controls | 0.257*** | (0.041) | 192,895 | 0.67 | 23.73 |
| | Controlling only for pre-period Sales | 0.190*** | (0.031) | 216,305 | 0.68 | 26.55 |
| | Balanced sample | 0.145*** | (0.033) | 151,984 | 0.35 | 18.36 |
| | Unbalanced sample | 0.163*** | (0.026) | 251,011 | 0.36 | 25.52 |
| | Non-Parametric Markups | 0.108*** | (0.024) | 208,956 | 0.65 | 25.61 |
| | Excluding crisis | 0.147*** | (0.032) | 168,750 | 0.62 | 21.84 |
| | Year-Sector-Region FE | 0.121*** | (0.023) | 206,417 | 0.48 | 29.08 |
| | Productivity control | 0.129*** | (0.026) | 208,855 | 0.48 | 25.71 |
| $T_{2,it}$ | Pre-period controls and their interactions with Post | 0.210*** | (0.035) | 208,956 | 0.37 | 18.07 |
| | Simultaneous controls | 0.277*** | (0.039) | 192,895 | 0.82 | 26.48 |
| | Controlling only for pre-period Sales | 0.307*** | (0.055) | 216,305 | 0.17 | 15.68 |
| | Balanced sample | 0.193*** | (0.043) | 151,984 | 0.20 | 12.12 |
| | Unbalanced sample | 0.226*** | (0.038) | 251,011 | 0.11 | 16.31 |
| | Non-Parametric Markups | 0.153*** | (0.030) | 208,956 | 0.30 | 17.16 |
| | Excluding crisis | 0.202*** | (0.041) | 168,750 | 0.28 | 15.14 |
| | Year-Sector-Region FE | 0.196*** | (0.026) | 206,417 | 0.23 | 31.96 |
| | Productivity control | 0.218*** | (0.032) | 208,855 | 0.15 | 28.27 |
| $T_{3,it}$ | Pre-period controls and their interactions with Post | 0.218*** | (0.034) | 208,956 | 0.61 | 22.57 |
| | Simultaneous controls | 0.304*** | (0.039) | 192,895 | 0.75 | 31.06 |
| | Controlling only for pre-period Sales | 0.300*** | (0.045) | 216,305 | 0.18 | 21.73 |
| | Balanced sample | 0.189*** | (0.037) | 151,984 | 0.14 | 15.67 |
| | Unbalanced sample | 0.223*** | (0.033) | 251,011 | 0.08 | 22.34 |
| | Non-Parametric Markups | 0.157*** | (0.028) | 208,956 | 0.43 | 22.63 |
| | Excluding crisis | 0.200*** | (0.037) | 168,750 | 0.39 | 21.01 |
| | Year-Sector-Region FE | 0.211*** | (0.024) | 206,417 | 0.07 | 42.78 |
| | Productivity control | 0.231*** | (0.029) | 208,855 | 0.10 | 39.02 |

*Notes:* The table provides a series of robustness checks of our baseline in Table 5. For each of the three treatment indicators, we report the main IV estimate and other relevant statistics when we alter the main specification in equation (22) with the list of changes described in the table. See the text for details.

Our main baseline result - positive and significant effect of intangibles on firm-level markups - is always confirmed. Overall, the different IV regressions are correctly specified, as is demonstrated by the reported F- and Hansen's J-statistic.

**Alternative IV strategy** Notwithstanding the use of these firm-specific controls, the results might still be affected by residual unobserved heterogeneity at the firm level. To address this concern, we consider an alternative IV strategy for estimating equation (22), aggregating observations at the region-industry level. We divide our sample into clusters defined by 4-digit NACE industries, bins of firm sizes, and administrative regions. Enforcement of the law capping payment terms is the responsibility of the seven Regional Directorates of the Ministry of the Economy (see Table A1 in the Appendix for the territorial partition). Due to potential differences in these regional directorates' efficiency, according to industry and firm size class, the legislation may have produced heterogeneous effects across different clusters.

Exploiting information on each firm's location, we build a DSO measure at the cluster level as

are available upon request.

the weighted mean of days of sales outstanding for firms in the cluster in the years before 2007. We then consider each cluster as treated if the average DSO of that cluster is above the 60-day threshold before 2007, and we use this as an instrument for intangibles. We then replicate our baseline exercise in equation (22) on this sample.

The results are given in Table A2 in the Appendix. We consider different sets of fixed effects: column (1) includes year times 4-digit industry fixed effects; column (2) includes year times 2-digit industry fixed effects. The results show that an increase in intangibles within a cluster leads to higher average markups. The estimated elasticities are of the same order of magnitude of those in Table 5. The alternative IV regressions are correctly specified, as is shown by the reported F- and Hansen's J-statistic.

## 5 Heterogeneous Pass-Through Effects

The third and final testable prediction of our theoretical model is that the pass-through of a marginal cost shock into markups is more extensive for firms with greater holdings of intangible assets or more financially capable firms. Our identification strategy consists of augmenting the baseline specification (22) with an interaction term between intangibles and the firm's ex-ante intangible investment or financial capability, which is arguably correlated with their ability to operate the fixed-cost technology. The identifying assumption is that firms with more ex-ante intangible assets or greater financial capability initially operate on a less elastic part of the demand function, such that they can pass a higher portion of the shock through to markups following the positive shock intangibles.

We consider several proxies for a firm's ex-ante intangible position. Our first measure is a dummy variable taking the value of 1 if the average share of intangibles in a firm's sale in the years before the policy shock is above the median in the same 4-digit industry and size class. We then follow Mulier et al. (2016), considering as an alternative proxy for ex-ante financial capability a simple index of firm age, size, cash flow, and leverage (ASCL). Thus, our proxy of financial capability is a dummy variable taking the value of 1 if the firm is above the median ASCL index in its 4-digit industry and size-class group in the years before the policy shock.[30] We consider the

[30] The ASCL index assigns a value of 0 (1) to each variable depending on whether a firm is scoring below (above)

following specification:

$$\ln \mu_{it} = \alpha + \beta_1 \ln(\text{Intan})_{it} + \beta_2 \ln(\text{Intan})_{it} \times \text{Fin. cap}_{i,Pre}$$
$$+\beta_3 \text{Fin. cap}_{i,Pre} + Post_t \times X_i'\gamma + X_{i(t)}'\lambda + \delta_{st} + \alpha + \epsilon_{it}. \tag{23}$$

Our coefficient of interest is $\beta_2$, the interaction between each firm's pre-shock financial capability and the intangible variables. As both the second and third term in the right-hand side of equation (23) are endogenous to the error term, we adopt an instrumental variable strategy where the first stage is a difference in difference in differences embracing all the interactions between the treatment variable ($T_{3,it}$), the post dummy, and the financial capability dummy. We control for the covariates already in the baseline estimation, namely firm-level sales, loans, cash flows and liabilities measured in the pre-shock period, and include industry×year fixed effects to account for industry-specific demand shocks. The results are reported in Table 7.

Table 7: Pass-through Heterogeneity

| | Dependent Variable: ln $\mu_{it}$ (Baseline) | |
|---|---|---|
| | (1) | (2) |
| ln Intan$_{it}$ [$T_{3,it}$×Post$_t$] | 0.216*** | 0.186*** |
| | (0.0213) | (0.0260) |
| ln Intan$_{it}$ [$T_{3,it}$×Post$_t$] × Dummy Int/Sales pre above median$_{it}$ | 0.0313*** | |
| | (0.00359) | |
| ln Intan$_{it}$ [$T_{3,it}$×Post$_t$] × Dummy ASCL pre above median$_{it}$ | | 0.00665** |
| | | (0.00274) |
| Obs. | 207,709 | 208,936 |
| $R^2$ | 0.147 | 0.305 |
| Year × Industry FE | Yes | Yes |
| Controls | $X_i$ | $X_i$ |
| F-Stat | 26.10 | 14.14 |
| Hansen J | 0.559 | 0.351 |

*Notes:* The table shows the IV coefficients obtained by running 2SLS on equation (23). Dependent variable: *ln $\mu_{it}$ (Baseline)* indicates firm-level markups following De Loecker and Warzynski (2012). *ln Intan$_{it}$* indicates (the log of 1+) firm-level intangible assets, measured as total firm expenditure on fixed costs. We instrument it with the interaction between (the log of) the difference between the pre-policy shock average DSO and DPO (replaced with zero when negative), $T_{3,it}$, and a dummy = 1 after the implementation of the policy, namely after 2009 (included), $Post_t$. *Dummy Int/Sales pre above median$_{it}$* is a dummy = 1 if the average share of intangibles over sales of a given firm before the policy shock is above the median of all firms in the same 4-digit industry and size class. *Dummy ASCL pre above median$_{it}$* is a dummy = 1 if the firm is above the median ASCL index (Mulier et al., 2016) in its 4-digit industry and size-class group before the policy shock. All specifications include Year×Industry fixed effects. The set of time invariant controls $X_i$ (measured in 2004) includes firm sales, cash flows, loans and liabilities. Kleibergen-Paap Wald F and Hansen J statistics are reported at the bottom of the table. Standard errors are in parentheses and clustered at the firm level, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The first row shows the elasticity of markups to intangibles. Consistent with the baseline estimates in Table 5, expenditures on intangibles are positively and significantly correlated with firm

the industry median. Firms with a higher value of ASCL are less likely to be affected by financial constraints, and thus have a greater financial capability. A similar index has been considered more recently by Cloyne et al. (2018).

Table 8: Pass-through Heterogeneity - Robustness

| Dependent Variable: | ln $\mu_{it}$ (NP) | | ln $\mu_{it}$ (Baseline) | | | |
|---|---|---|---|---|---|---|
| Sample: | Baseline sample | | Balanced sample | | Unbalanced sample | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| ln Intan$_{it}$ [T$_{3,it}$×Post$_t$] | 0.188*** | 0.151*** | 0.188*** | 0.184*** | 0.226*** | 0.196*** |
| | (0.0191) | (0.0226) | (0.0230) | (0.0340) | (0.0195) | (0.0239) |
| ln Intan$_{it}$ [T$_{3,it}$×Post$_t$] × Dummy Int/Sales pre above median$_{it}$ | 0.0275*** | | 0.0273*** | | 0.0308*** | |
| | (0.00321) | | (0.00379) | | (0.00347) | |
| ln Intan$_{it}$ [T$_{3,it}$×Post$_t$] × Dummy ASCL pre above median$_{it}$ | | 0.00709*** | | 0.00509* | | 0.00951*** |
| | | (0.00247) | | (0.00285) | | (0.00272) |
| Obs. | 207,709 | 208,936 | 151,301 | 151,967 | 249,064 | 250,979 |
| Year × Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | $X_i$ | $X_i$ | $X_i$ | $X_i$ | $X_i$ | $X_i$ |
| F-Stat | 26.10 | 14.14 | 18.57 | 7.957 | 29.53 | 16.16 |
| Hansen J | 0.259 | 0.578 | 0.418 | 0.381 | 0.267 | 0.0501 |

*Notes:* The table shows the IV coefficients obtained by running 2SLS on equation (23). Dependent variables: columns (1)-(2), *ln* $\mu_{it}$ *(NP)* indicates a non-parametric markup measure (obtained by proxying the output elasticities by the average input cost share at the industry-year level); columns (3)-(6), *ln* $\mu_{it}$ *(Baseline)* indicates firm-level markups following De Loecker and Warzynski (2012). In columns (1) and (2) we use our baseline sample (firms that enter before 2005 and exit after 2010), in columns (3) and (4) the balanced sample (firms those firms that are always present over the sample period), and in columns (5) and (6) the unbalanced sample (original). *ln Intan*$_{it}$ indicates (the log of 1+) firm-level intangible assets, measured as total firm expenditure on fixed costs. We instrument it with the interaction between (the log of) the difference between the pre-policy shock average DSO and DPO (replaced with zero when negative), $T_{3,it}$, and a dummy = 1 after the implementation of the policy, namely after 2009 (included), $Post_t$. *Dummy Int/Sales pre above median*$_{it}$ is a dummy = 1 if the average share of intangibles over sales of a given firm before the policy shock is above the median of all firms in the same 4-digit industry and size class. *Dummy ASCL pre above median*$_{it}$ is a dummy = 1 if the firm is above the median ASCL index (Mulier et al., 2016) in its 4-digit industry and size-class group before the policy shock. All specifications include Year×Industry fixed effects. The set of time invariant controls $X_i$ (measured in 2004) includes firm sales, cash flows, loans and liabilities. Kleibergen-Paap Wald F and Hansen J statistics are reported at the bottom of the table. Standard errors are in parentheses and clustered at the firm level, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

markups. The second and third rows report the coefficients of the interaction term between intangibles and the financial capability proxy (intangibles over sales and ASCL, respectively). In line with the model's predictions, the pass-through to markups of the marginal cost shock induced by intangible investment is larger for those firms whose ex-ante intangible holdings and/or financial capability were above median, as shown by the positive and significant sign of the interaction term in both columns (1) and (2). The IV regression seems to be correctly specified, with both the F-test of weak instruments and the Hansen J-test of overidentification above the conventional critical thresholds.

**Robustness** We run a number of robustness checks of our heterogeneous pass-through result in Table 8. Columns 1 and 2 take our alternative, non-parametric measure of markups as the dependent variable. Columns 3 to 6 repeat the analysis on the fully balanced and the unbalanced sample of firms, respectively. The main results are broadly confirmed across specifications.[31]

Taken together, the results in this section show evidence of financially-driven heterogeneity in pass-through elasticities across firms.

[31] Note however that the Hansen-J test of overidentification is not satisfied when we use the unbalanced sample of firms. This result is not surprising, in light of the substantial attrition observed in our data.

# 6 Alternative Mechanisms and General Implications

This section critically appraises two key issues of our identification strategy and touches on our findings' external validity. First, we substantiate the claim that intangibles are more sensitive to liquidity constraints than other capital investment forms. We then address the concern that markups may be affected by the policy shock through channels other than intangible investment. In doing so, we validate the exclusion restriction of the instrumental variable strategy adopted in sections 4.3 and 5. Finally, we discuss some broader implications of our study, relating our findings with several other studies of the evolution of intangibles and markups in the U.S. vs. the EU, and across EU countries.

**Liquidity Shock and Tangible Assets** One legitimate concern is that in our model, the liquidity shock only affects intangible investment. In reality, of course, all types of investments may well be affected by financial factors. Figure A3 in the Appendix addresses this issue. It replicates the exercise in Figure 6, but using different proxies of fixed assets as the dependent variable.[32] Where Figure 6 showed a statistically and economically significant effect of the policy shock on intangibles, the same does not apply to tangible capital. This result is robust to alternative definitions of fixed assets. In the left panel of Figure A3, the dependent variable is the log of *total fixed assets* multiplied by the user cost of capital; in the right panel, fixed assets are defined as the log of *tangible fixed assets* times the user cost. Our results empirically validate the thesis that greater dependence on intangibles distorts firms' ability to raise external capital, most likely owing to the difficulties of using this type of asset as loan collateral.[33]

**What does our policy shock reflect?** A second, major concern is that intangible capital accumulation is the model's only source of markup dynamics. This assumption underlies the exclusion restriction of the IV strategy for testing our second and third predictions, i.e., the thesis that the policy shock affects markups exclusively through its impact on intangible investment. Suppose marginal costs respond to other forces triggered by the shock. In that case, our estimation will still

[32] To be consistent with the main empirical exercise, in all robustness regressions controls for the beginning-of-the-sample period levels of the variable unser investigation. In case of Figure A3, we add a control for the beginning-of-the-sample period level of fixed assets. Results are not qualitatively affected by excluding these controls.

[33] See, e.g. Hall and Lerner (2010); Loumioti (2012); Haskel and Westlake (2018).

interpret such actions through the intangible accumulation lens, not the actual economic process driving the decisions. One potentially important factor that may also be affected by the shock to payment terms is firms' bargaining power vis-à-vis their customers. If this is so, the policy change work its effect directly on markups, rather than on intangibles as we claim.

We provide evidence for our identification assumption in two steps. First, we show that the policy shock does appear to shock cash holdings, over and above other financial factors. Figure A4 shows the effect on different financial variables observed in firm-level accounts: cash, loans, and non-current liabilities. The figure displays the 99% confidence areas for the coefficients $\pi_j$, obtained from running OLS on the following equation:

$$\ln Y_{it} = \sum_{j=2004}^{2014} \pi_j \cdot T_{3,ij} + X_i' \lambda + \delta_{st} + \alpha + \epsilon_{it}, \tag{24}$$

where $Y_{it} = \{Cash_{it}, Loans_{it}, NCliab_{it}, Cliab_{it}\}$. As in our main analysis, we take $T_{3,it}$ as our definition of the treatment variable, and we apply the baseline specification, which has only time-invariant controls $X_i$. The figure shows that among all the observed financial variables, the one that seems to be most directly affected by the policy shock is a firm's cash holdings, which is consistent with our interpretation of the reform as essentially a shock to liquidity.

We then perform the same exercise on several other firm strategic variables: markups, revenue productivity, employment and export behavior. Figure A5 shows the 99% confidence areas for the coefficients $\pi_j$, obtained by running OLS on equation (24) with these dependent variables.[34] The policy shock does not appear to directly affect any of these firm-level variables, except markups, where the effect is significant statistically, but not economically, given the magnitude of the coefficient. We interpret Figures A4 and A5 as evidence in favor of our central assumption, namely that the policy shock acted as a shock to firm liquidity and affected markups only indirectly through the impact on investment in intangible assets. While we cannot completely preclude the role of other factors in determining the main results, owing to data limitations, the evidence presented here suggests that these confounding factors should play only a minor role.

[34] The control vector in this case includes beginning-of-the-period employment, export value and capital.

**General Implications** Our results are consistent with a growing literature looking at the cross-country evolution of intangibles and markups. Corrado et al. (2018) use a newly revised and updated release of the INTAN-Invest dataset for 18 European countries and the U.S. to analyze intangible investment diffusion within countries. They show that the total average share of intangibles as a share of GDP in 2002-2013 is more extensive in the U.S. (8.8%) than the E.U. (7.2%). Within the E.U., countries like France at 8.7% are above average, while countries like Italy (5.3%) and Spain (4.6%) are below average. Notably, while the financial crisis of 2008-09 had only a minor negative impact on the evolution of intangibles in the U.S. and France, where it has seen a sustained growth after 2009, the intangible dynamics have remained flat after 2009 in Italy and Spain.[35] This cross-country evidence is consistent with one of our paper's key results, which says that adverse financial conditions hamper intangible investment. Financial conditions have significantly improved in the U.S. after 2009. Similarly, France enacted in 2009 extensive measures to support firm liquidity, as discussed above. On the contrary, Italy and Spain have seen a worsening of their financial conditions after 2009.

To provide some firsthand evidence of these cross-country correlations, we build representative firm-level samples for Italy and Spain, with the same procedures and sources on our French data.[36] Figure A6 shows the correlation between intangibles and financial conditions using firm-level data in the three countries. On the horizontal axis, we report a measure of country-year financial stress (the *Country Level Index of Financial Stress* as measured by the ECB), normalized to 100 in 2004. We report the (weighted) average investment of intangibles by firms in each country-year pair on the vertical axis. The Figure shows that after 2009, France experiences significantly less financial stress and deeper investment in intangibles than Italy and Spain.

We then relate intangible investment to markups to provide some cross-country evidence of our paper's second main result. Consistent with our thesis, Figure A7 shows that average markups in France recover more quickly after the financial crisis than markups in Italy and Spain.[37]

[35]The average share of intangibles is shown in Table 2 in Corrado et al. (2018). The reported evolution over time is shown in Figure 2 and Figure 5 of the same paper.

[36]Details available on request.

[37]Looking at the general evolution of markups in the U.S. vs. the E.U., De Loecker and Eeckhout (2018) find that U.S. markups are on average higher than E.U. ones. However, they both tend to rise over time. Gutiérrez and Philippon (2017) show that profits margins have increased in the U.S. but they have remained stable or decreased in Europe; they also show that the rise of profits margins in the U.S. is associated with a significant shift towards intangible capital, more pronounced than in the EU.

While anecdotal, our cross-country results further support our thesis that financial factors, through the intangible investment channel, are an essential and largely overlooked source of differences in markups between firms and, ultimately, countries.

## 7 Conclusions

We discuss the link between financial factors, investment in intangibles, and firm-level markups. We propose a theoretical explanation of the relationship between these variables positing imperfect financial markets and variable demand elasticity. Firms can invest in a cost-reducing technology (akin to intangible capital), but heterogeneous financial frictions distort this decision, leading to endogenous dispersion in markups. We show theoretically that financial variables operate both at the extensive margin, acting as a barrier to investment entry, and at the intensive margin, distorting individual firms' level of investment. We find evidence of the causal relationship between the intensive margin effect of heterogeneous financial frictions on intangibles and markups. The study exploits a quasi-natural experiment created by the enforcement of a commercial policy reform in France in 2009 that substantially shortened payment terms for a certain group of firms, increasing their liquidity.

Our results carry two policy implications. First, the documented trends in markups in modern economies may stem from the increasing importance of intangible assets. In turn, the pronounced difference in markup trends between U.S. and European firms in the last decade may be partly explained by more substantial intangible capital investment by U.S. firms. Second, access to finance is a critical component in firms' ability to invest in intangible assets. Heterogeneity in financial access may lead to sub-optimal investment in intangibles, high markup dispersion, and misallocation of capital in the economy.

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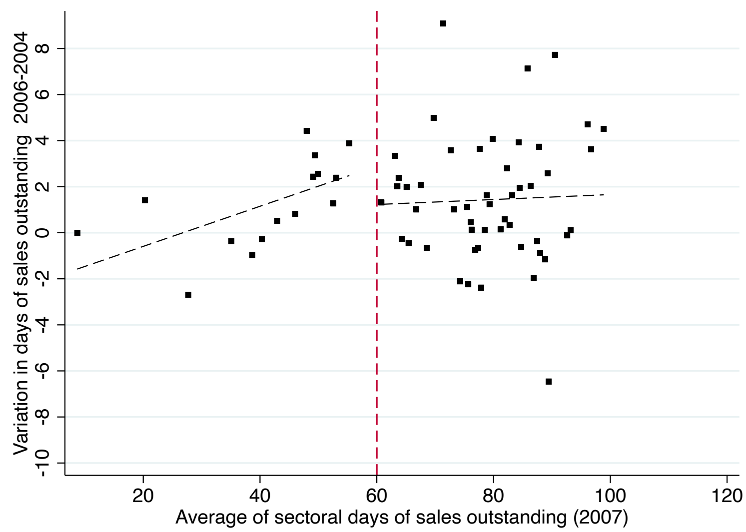
# A Additional Figures and Tables

Figure A1: Impact of the policy on payment days, 2004-2006




*Notes:* This graph displays the difference in days of sales outstanding between 2004 and 2006 as a function of the average DSO in 2004 for each NACE-4 digit industry. DSO is computed as the firm-level ratio of accounts receivable over sales multiplied by 365. The data set is split in 100 percentiles along the x-axis; the ordinate axis represents the average value of the y variable in each percentile.

Figure A2: Intangibles and Liquidity, Different Treatment Definitions

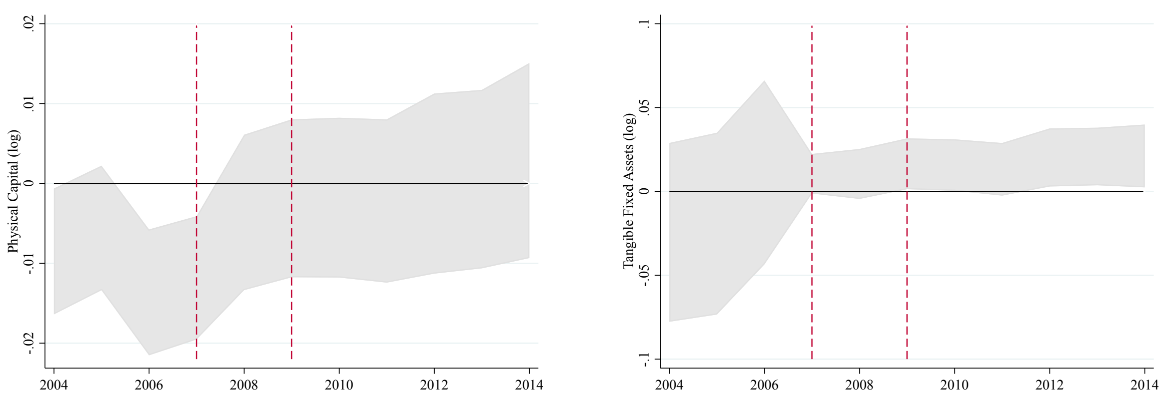

*Notes:* The graph displays the coefficients $\pi_j$, with 95% confidence intervals, obtained from estimating equation (20) using OLS. 'Dummy treatment' refers to treatment definition $T_{2,it}$, while 'continuous treatment' refers to treatment definition $\ln T_{3,it}$.

Table A1: Regional enforcement of the policy

| Regional directorate | Region |
|---|---|
| Direction régionale du Nord | Nord - Pas-de-Calais<br>Picardie |
| Direction régionale de Lorraine | Champagne-Ardenne<br>Lorraine<br>Alsace |
| Direction régionale de Rhône-Alpes | Bourgogne<br>Franche-Comté<br>Rhône-Alpes<br>Auvergne |
| Direction régionale de Provence-Alpes-Côte d'Azur | Languedoc-Roussillon<br>Provence-Alpes-Côte d'Azur<br>Corse |
| Direction régionale d'Aquitaine | Aquitaine<br>Midi-Pyrénées<br>Limousin<br>Poitou-Charentes |
| Direction régionale des Pays de la Loire | Bretagne<br>Pays de la Loire<br>Centre |
| Direction régionale d'Ile-de-France | Ile-de-France<br>Basse-Normandie<br>Haute-Normandie<br>Réunion<br>Mayotte<br>Saint-Pierre-et-Miquelon |

*Notes:* This table shows the allocation of the regional directorates of the to the NUTS2-regions in France as described in *Décret no. 2009-1377 du 10 novembre 2009 relatif à l'organisation et aux missions des directions régionales des entreprises, de la concurrence, de la consommation, du travail et de l'emploi, Annexe I.*

Figure A3: Liquidity Shock and Tangible (Fixed) Assets




**a)** *Physical Capital* **b)** *Tangible Fixed Assets*

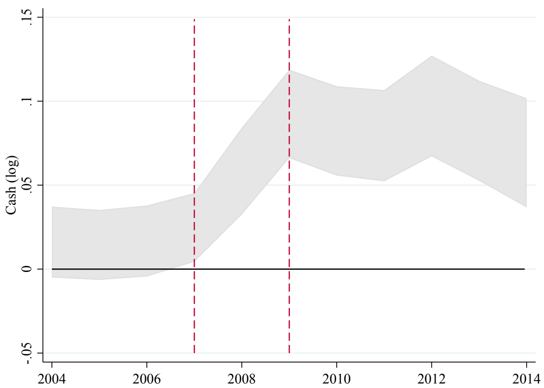
*Notes:* The graph displays the coefficients $\pi_j$, with 99% confidence intervals, obtained from estimating equation $\ln Y_{it} = \sum_{j=2004}^{2014} \pi_j \cdot T_{3,ij} + X_i'\lambda + \delta_{st} + \alpha + \epsilon_{it}$ using OLS. The variable $Y$ is given by (log) physical capital expenditures, measured as total fixed assets times user cost of capital, and (log) tangible fixed asset expenditures, measured as tangible fixed assets times user cost of capital. The set of controls $X_i$ include the same controls as in our baseline specification, plus a control for (log) fixed assets measured in the first year of the sample (2004).

Table A2: Baseline regression with regional interaction

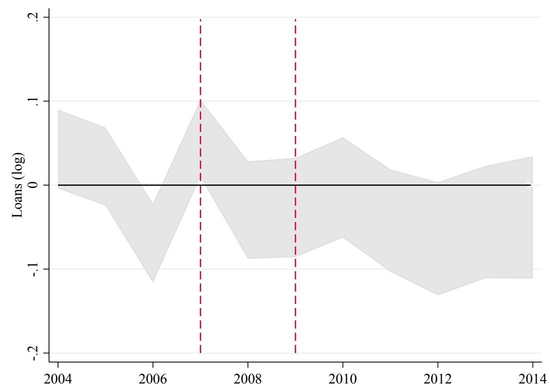
| | Dependent Variable: ln $\mu_{it}$ (Baseline) | |
|---|---|---|
| | (1) | (2) |
| ln Intan$_{it}$ | 0.113*** | 0.181*** |
| | (0.0289) | (0.0581) |
| Obs. | 208,956 | 209,040 |
| R2 | 0.459 | 0.267 |
| Year $\times$ Industry 4 digits FE | Yes | No |
| Year $\times$ Industry 2 digits FE | No | Yes |
| Region FE | Yes | Yes |
| Controls | $X_i$ | $X_i$ |
| F-Stat | 10.97 | 32.00 |
| Hansen J | 0.803 | 0.306 |

*Notes:* The table shows the IV coefficients obtained by running 2SLS on equation (22). Dependent variable: *ln* $\mu_{it}$ *(Baseline)* indicates firm-level markups following De Loecker and Warzynski (2012). *ln* $Intan_{it}$ indicates (the log of 1+) firm-level intangible assets, measured as total firm expenditure on fixed costs. We instrument it with the interaction between the industry-level treatment, $DSO_{industry}$, and a dummy = 1 after the implementation of the policy, namely after 2009 (included), $Post_t$. $DSO_{industry}$ is defined as follows: we divide our sample into clusters defined by the NACE-4 digit industries, bins of firms' size and the Regional Directorates, then we build a measure of DSO at the cluster level as the weighted mean of days of sales outstanding of firms in the cluster, in the years before 2007; $DSO_{industry}$ assumes value 1 if the average DSO of that cluster is above the 60-day threshold before 2007. All specifications include Regional Directorates fixed effects, column (1) includes Year$\times$Industry 4 digits fixed effects, while column (2) includes Year$\times$Industry 2 digits fixed effects. The set of time invariant controls $X_i$ (measured in 2004) includes firm sales, cash flows, loans and liabilities. Kleibergen-Paap Wald F and Hansen J statistics are reported at the bottom of the table. Standard errors are in parentheses and clustered at the firm level, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$.

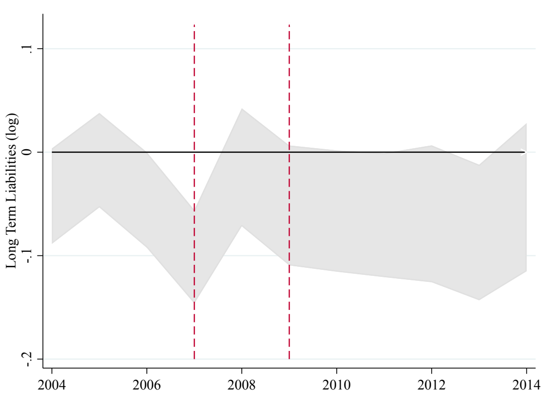
Figure A4: Liquidity Shock and Financial Variables



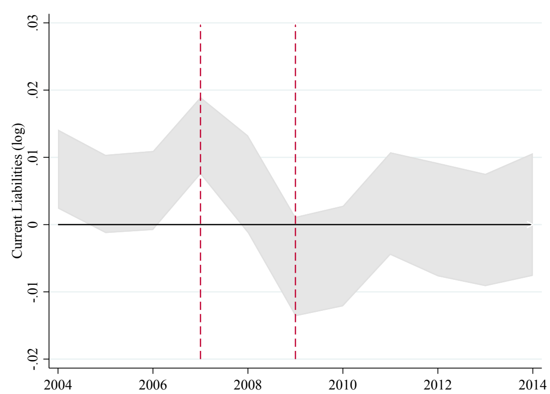

**a)** *Cash*




**b)** *Loans*



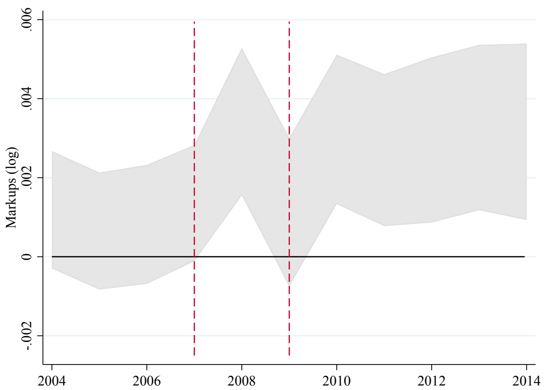

**c)** *Non current liabilities*



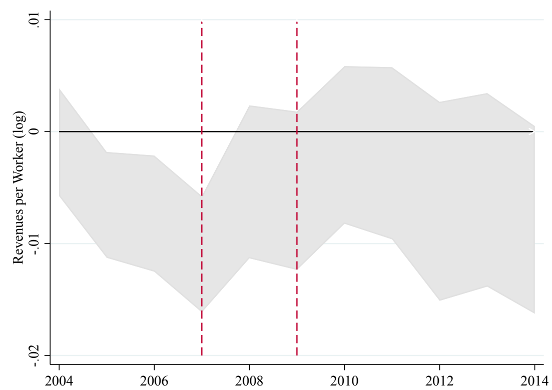

**d)** *Current liabilities*

*Notes:* The graph displays the coefficients $\pi_j$, with 99% confidence intervals, obtained from estimating equation $\ln Y_{it} = \sum_{j=2004}^{2014} \pi_j \cdot \ln T_{3,ij} + X_i'\lambda + \delta_{st} + \alpha + \epsilon_{it}$ using OLS. The variable $Y$ is given by (log) cash, (log) loans, (log) non current liabilities and (log) current liabilities, respectively. The set of controls $X_i$ include the same controls as in our baseline specification, plus a control for (log) non-current liabilites and cash measured in the first year of the sample (2004).

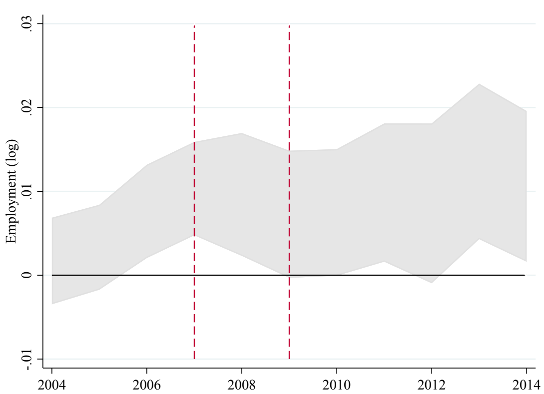
Figure A5: Liquidity Shock and Real Variables



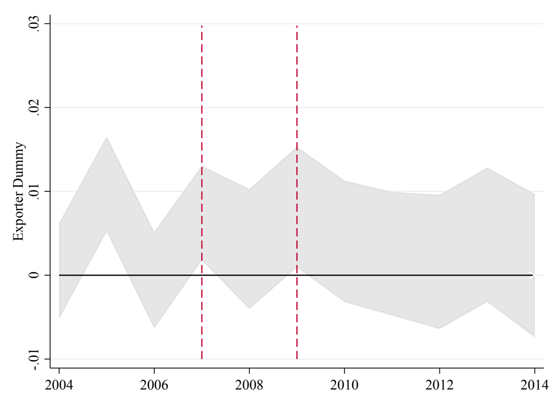

**a)** *Markups*




**b)** *Revenue Productivity*



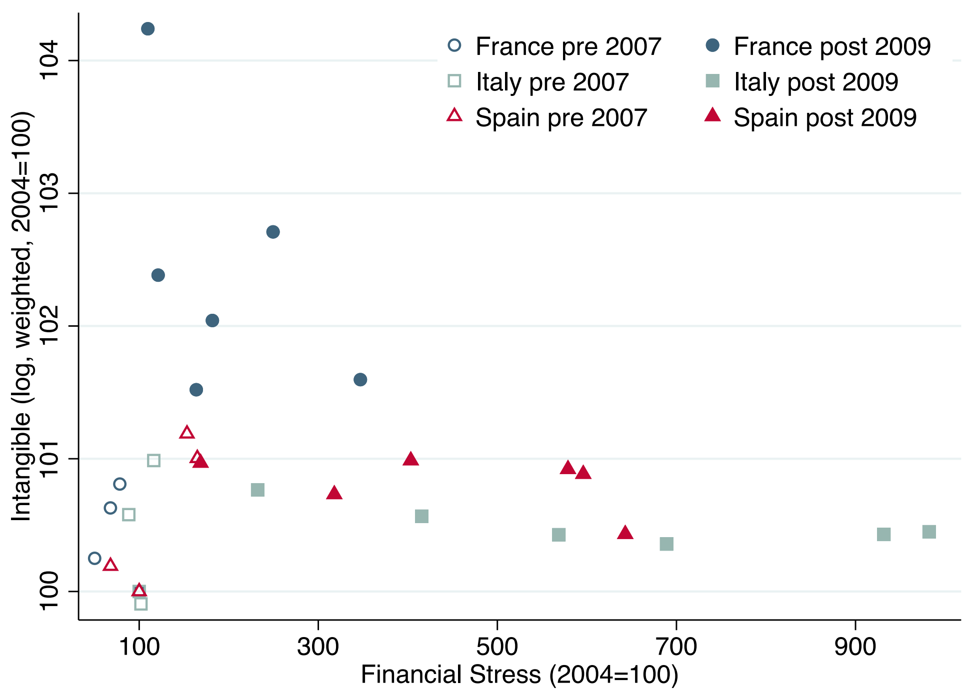

**c)** *Employment*




**d)** *Export Behavior*

*Notes:* The graph displays the coefficients $\pi_j$, with 99% confidence intervals, obtained from estimating equation $\ln Y_{it} = \sum_{j=2004}^{2014} \pi_j \cdot T_{3,ij} + X_i'\lambda + \delta_{st} + \alpha + \epsilon_{it}$ using OLS. The variable $Y$ is given by (log) baseline markups, (log) revenue productivity, (log) employment and a dummy equal to 1 if the firm is an exporter, respectively. he set of controls $X_i$ include the same controls as in our baseline specification, plus a control for (log) employment, capital and exports measured in the first year of the sample (2004).

Figure A6: Intangibles and Financial Stress




*Notes:* The graph displays on the horizontal axis a country and year-specific measure of financial stress (Country Level Index of Financial Stress as measured by the ECB), normalized to 100 in 2004, while on the vertical axis the (weighted) average investment of intangibles by firms in each country-year pair.

Figure A7: Markups' Dynamic


*Notes:* The graph displays the dynamic of (weighted) markups over time.

## B Estimation of Firm-level Markups

In this section, we describe our procedure for estimating measures of markups at the firm-level building on De Loecker and Warzynski (2012). We start by describing our production function estimation procedure, and then describe markups estimation in section B.2.

### B.1 Production Function Estimation

We consider the following class of production technologies for firm $i$ at time $t$:

$$Q_{it} = \exp(\omega_{it} + \phi(s_{it}) + \epsilon_{it}) F_t(K_{it}, \mathbf{V}_{it}; \beta), \tag{25}$$

where $Q_{it}$ is physical output, obtained using capital ($K_{it}$), and a set of variable inputs such as labor, intermediate inputs, and materials which is captured by the vector $\mathbf{V}_{it} = (V_{it}^1, V_{it}^2 ..)$. The function $F(\cdot)$ satisfies standard regularity conditions. The term $\omega_{it}$ reflects a Hicks-neutral firm-specific productivity term, while $\phi_{it} = \phi(s_{it})$ is the productivity advantage of firms that invest in intangibles. Both $\omega_{it}$ and $\phi_{it}$ are observed by the firm when choosing inputs. The term $\epsilon_{it}$ captures measurement error and idiosyncratic shocks to production unobserved to the firm.

Note that in our theoretical model, for simplicity, we abstracted from the term $\omega_{it}$ and implicitly assumed $\omega_{it} = 0$, meaning that firm-level production efficiency is a one-to-one function of intangible expenditures. Our production function estimation procedure relaxes this assumption and considers the more general case where firms have different production efficiencies, even conditional on their intangibles holdings.

Neither $\omega_{it}$ nor $\phi_{it}$ nor $\epsilon_{it}$ are observed by the researcher. However, we can observe a measure of total expenditures on fixed costs, which we denote as $Intan_{it}$, which is positively related to the unobserved productivity term according to our theoretical model. We depart slightly from the theoretical model and allow $\phi_{it}$ to depend both on the fixed cost expenditures and the unobserved productivity term $\omega_{it}$. We allow for this dependence in the empirical analysis by writing $\phi_{it} = h(\ln Intan_{it}, \omega_{it})$.

Even though for our main results we consider more flexible translog production functions, in what follows we assume a Cobb-Douglas specification for expositional purposes. We thus write

(25) in explicit form as:

$$q_{it} = \beta_k k_{it} + \beta_v v_{it} + h(\omega_{it}, \ln Intan_{it}) + \epsilon_{it}, \tag{26}$$

where $h(\omega_{it}, \ln Intan_{it})$ is the productivity term written in compact form and where lower-case letters denote log variables. Because in the empirical implementation we measure variable inputs as tocal cost of goods sold, in the exposition we treat the vector $\mathbf{V}$ as a scalar $V$.

AAs it is well-known in the literature, the estimation of (26) requires dealing with several biases. Not only do we have to deal with the unobserved term $\omega$, but because we only observe nominal measures of inputs and output, we also have to deal with well-known price biases in the estimation, potentially large when markups are heterogeneous across firms (De Loecker and Goldberg, 2014; Foster et al., 2008).

Because we do not observe input prices, we impose the following assumption:

**A1** *Firms take the price $W_{it}^X$ of inputs $X = K, V$ as given.*

Under assumption A1, input quantities can be consistently measured as deflated expenditures, provided that exogenous differences in input prices across firms are not too large (De Loecker et al., 2016). Dealing with the output price bias is more complicated, as in the model we explicitly allow for markup differences across firms. Let us rewrite output $q_{it}$ as deflated revenues $\tilde{r}_{it} = r_{it} - p_{st}$, where $r_{it}$ is the (observed) log revenues of firm $i$, and $p_{st}$ is the (log) deflator for output of firms in each 2-digit sector $s$. Notice that this means that: $q_{it} = \tilde{r}_{it} - (p_{it} - p_{st})$, where the term $(p_{it} - p_{st})$ represent the deviation of the unobserved firm-level price from the sectoral price.

We substitute this information in (26) to write:

$$\tilde{r}_{it} = \beta_k k_{it} + \beta_v v_{it} + h(\omega_{it}, \ln Intan_{it}) + (p_{it} - p_{st}) + \epsilon_{it}.$$

The term $(p_{it} - p_{st})$ is unobserved, and correspond to the output price bias.

Using the insights from the theoretical model, we can write this unobserved term as:

$$p_{it} - p_{st} = \mu\left(p_{it} - p_{st}\right) + c_{it} - p_{st},$$

where $c_{it}$ is (log) marginal cost, which depends on input prices and production efficiency, e.g.

$c(\mathbf{w}_{it}, h(\omega_{it}, \ln Intan_{it}))$, where $\mathbf{w}_{it}$ is the vector of firm-level input unit prices. Therefore, we can solve for the unobserved term $p_{it} - p_{st}$ as:

$$(p_{it} - p_{st}) = p(\mathbf{w}_{it}, p_{st}, h(\omega_{it}, \ln Intan_{it})).$$

Substituting into the estimating equation, we get:

$$\tilde{r}_{it} = \beta_k \tilde{k}_{it} + \beta_v \tilde{v}_{it} + H(\mathbf{w}_{it}, \omega_{it}, \ln Intan_{it}, p_{st}) + \epsilon_{it}, \tag{27}$$

where $H(\mathbf{w}_{it}, \omega_{it}, \ln Intan_{it}, p_{st}) = h(\omega_{it}, \ln Intan_{it}) + p(\mathbf{w}_{it}, p_{st}, h(\omega_{it}, \ln Intan_{it}))$, and $\tilde{x}_{it}$ for $x = v, k$ denotes deflated input expenditures. The only unobserved terms in equation (27) is now $\omega_{it}$. We follow the literature and rely on a control function approach, paired with an AR(1) process for productivity $\omega_{it} = g(\omega_{it-1} + \xi_{it}$ to estimate the output elasticity of the variable input $\beta_v$. We follow Ackerberg et al., 2015 and assume that the (unobserved) productivity term is given by a function of the firm's inputs and a control variable, namely $\omega_{it} = \omega(\tilde{v}_{it}, \tilde{k}_{it})$.

Putting all pieces together, we obtain:

$$\tilde{r}_{it} = \beta_k \tilde{k}_{it} + \beta_v \tilde{v}_{it} + \bar{H}(\mathbf{w}_{it}, \tilde{v}_{it}, \tilde{k}_{it}, \ln Intan_{it}) + \epsilon_{it}, \tag{28}$$

The polynomial $\bar{H}(\cdot)$ is a function of observable objects, and correct for unobserved output prices and productivity $\omega_{it}$ and $\phi_{it}$. We estimate (28) using the procedure in Wooldridge (2009). The identifying restrictions are that the TFP process's innovation is not correlated with current capital and with last period variable inputs. These moment conditions are fully standard in the production function estimation literature (Ackerberg et al., 2015).

**Productivity** Note that our discussion implies that physical productivity $TFPQ_{it} \equiv (\omega_{it} + \phi_{it})$, cannot be recovered from our procedure. We can identify an estimate of the term $\hat{H}$, which can be obtained as the residual of equation (28). This term reflects both physical efficiency and the average price of firm $i$, and is thus a measure of total factor revenue productivity. Although imperfect, we use this residual to control for unobserved productivity in the main empirical analysis.

## B.2 Markups

Once we have estimated the main elasticities, we can proceed to compute markups. We rely on a recently proposed framework by De Loecker and Warzynski (2012), based on the insight of Hall (1987) to estimate (firm-level) markups using standard balance sheet data on firms, which does not require to make assumptions on demand and how firms compete.

We consider the problem of a firm producing using a technology as in (25) and choosing inputs so as to minimize variable costs. The first order condition associated with the choice of the variable input can be written as:

$$\mu_{it} = \frac{\theta_{it}^{v}}{\alpha_{it}^{v}},$$

where $\theta_{it}^{v} = dq_{it}/dv_{it}$ is the output elasticity of the variable input and $\alpha_{it}^{v} \equiv \frac{E_{it}^{v}}{R_{it}}$ is the share of expenditures on variable inputs $E_{it}^{v}$ over total firm revenues $R_{it}$. We consider a translog specification of equation (25) for our baseline estimation, which implies that the output elasticity of the variable input can be obtained as:[38]

$$\hat{\theta_{it}^{v}} \equiv \frac{dq_{it}}{dv_{it}} = \hat{\beta}_{v} + 2\hat{\beta}_{vv}v_{it} + \hat{\beta_{kv}}k_{it}.$$

Markups are then computed as:

$$\hat{\mu}_{it} = \hat{\theta_{it}^{v}} \left(\frac{E_{it}^{v}}{R_{it}}\right)^{-1}.$$

[38] I write the TL as a second order polynomial in all inputs, i.e.

$$q_{it} = \beta_{k}k_{it} + \beta_{v}v_{it} + \beta_{kk}k_{it}^{2} + \beta_{vv}v_{it}^{2} + +\beta_{kv}k_{it}v_{it}.$$

The outout elasticity of the variable input can be then obtained as:

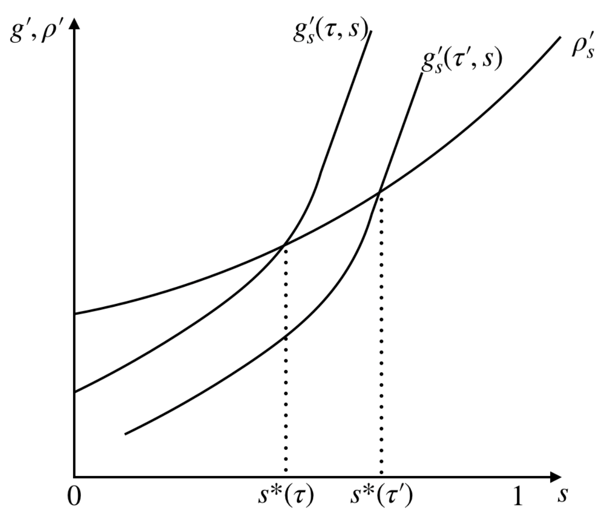
$$\theta_{it}^{v} = \frac{dq_{it}}{dv_{it}} = \beta_{v} + 2\beta_{vv}v_{it} + \beta_{kv}k_{it}$$

## C Theoretical results

### C.1 Derivation of Testable Prediction 1

Let $\rho(s) = (\mu(s) - 1)(1 - s)QD(y(s)))$ denote firm net revenues, where $y \equiv p/P$ is the variable price. Let $g(s, \tau) = (1 + \tau^{-1})f(s)$ be the effective cost of investment, expressed as a function of $s$. The first order condition for the optimal choice of intangibles is $\rho'_s = (1 + \tau^{-1})f'_s$. Given our regularity conditions on both the functions $D(\cdot)$ and $f(\cdot)$, the functions in both sides are everywhere continuous. The left hand side can be found as $\rho'_s = QD(y(s)) > 0$, while the right hand sideis given by $g'_s = (1 + \tau^{-1})f'_s > 0$. Moreover, it is easy to show that the assumptions on demand imply $\rho''_s = \frac{Q\varepsilon D(y)}{(1+\Gamma_i)(1-s_i)} > 0$ and $\rho'''_s = \frac{QD}{(1+\Gamma_i)(1-s_i)}\left[\varepsilon' D - D'\varepsilon - \varepsilon\frac{(1-s)\Gamma' - \Gamma}{(1+\Gamma_i)(1-s_i)}\right] > 0$. Similarly, we find $g''_s = (1 + \tau^{-1})f''_s > 0$, and $g'''_s = (1 + \tau^{-1})f'''_s > 0$, which says that both functions are increasing and convex. For small values of $s$, for an equilibrium to exists we must have that $\rho'_s > (1 + \tau^{-1})f'_s$, otherwise no firms would decide to invest in intangibles. Similarly, for large values of $s$, the cost of eliminating marginal costs completely must be infinite, such that all firms have positive marginal costs in equilibrium. This means that costs must grow faster than revenues for a high enough value of $s$. Graph C1 plots the equilibrium in this market, for two different values of $\tau$, with $\tau' > \tau$.

Figure C1: Equilibrium value of $s$




*Notes:* The graph shows dynamic of $s$, $g'$, and $\rho'$, for two different values of $\tau$, with $\tau' > \tau$.

For more financially capable firms, the effective cost of investment is shifted downward, such that they optimally choose a higher value.

## C.2 Derivation of Testable Prediction 2

The optimal price satisfies $p = \frac{\varepsilon(p/P)}{\varepsilon(p/P)-1}(1-s)$, which can be written in log terms as $\ln p = \ln \mu(p/P) + \ln(1-s)$. We denote by $\Gamma \equiv -\frac{d \ln \mu(y)}{d \ln y} = \Gamma(y)$ the markup elasticity to relative price $y$, and log differentiate to write $d \ln p = -\Gamma(s)\,(d \ln p - d \ln P) - \frac{s}{1-s} d \ln s$. Using simple algebra, it is easy to show thatt:

$$d \ln p = -\frac{s}{(1+\Gamma(s))(1-s)} d \ln s + \frac{\Gamma(s)}{1+\Gamma(s)} d \ln P.$$

Similarly, the optimal markup can be found as:

$$d \ln \mu \equiv d \ln p - d \ln(1-s) = \frac{\Gamma(s)}{1+\Gamma(s)} \frac{s}{(1-s)} d \ln s + \frac{\Gamma(s)}{1+\Gamma(s)} d \ln P.$$

It follows that

$$\frac{d \ln \mu}{d \ln s} = \frac{\Gamma(s)}{1+\Gamma(s)} \frac{s}{(1-s)} > 0 \tag{29}$$

Testable prediction 2 follows immediately from (29).

## C.3 Derivation of Proposition 3

Let us express equation (29) as a function of $\tau$ :

$$\frac{d\mu(\tau)}{d\tau} = \tilde{\Gamma}(\tau) \frac{\mu(\tau)}{1-s(\tau)} \frac{ds(\tau)}{d\tau} > 0, \tag{30}$$

where $\Gamma(\tilde{\tau}) \equiv \frac{\Gamma(\tau)}{1+\Gamma(\tau)}$ is such that $\tilde{\Gamma}'_{\tau} = \tilde{\Gamma}'_s s' < 0$. We take derivatives on both sides and write: and $\mu'_s > 0$

$$\frac{d^2\mu(\tau)}{d^2\tau} = \tilde{\Gamma}\mu s' \frac{(\frac{\tilde{\Gamma}'_s}{\tilde{\Gamma}} s \frac{s'}{s} \cdot + \frac{\mu'_s}{\mu} s \frac{s'}{s} + \frac{s''}{s'}) + 1}{(1-s)^2} > 0, \tag{31}$$

which is true whenever $\frac{d\ln\mu}{d\ln s} - \frac{d\ln\Gamma}{d\ln s} > 0$, namely, when markups are not too convex. This condition requires than markups vary across firms more than markup elasticities (and pass-through elasticities thereof) do. This condition is satisfied in existing studies of heterogeneous pass-through (Berman et al., 2012).

More simply, the result in equation 31, which is the basis of testable prediction 3, follows from our assumption that the Marshall's strong law of demand holds, namely, that pass-through of marginal cost shocks into markups are higher for firms with the lowest marginal costs.

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