Markups, Intangible Capital and Heterogeneous Financial Frictions*

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Abstract

This paper studies the interaction between financial frictions and intangible investment decisions in manufacturing firms and its implications for the dynamics of markups. We build a theoretical model in which heterogeneous credit constraints distort the decision of firms to invest in a cost-reducing technology. The resulting dispersion in marginal costs interacts with variable demand elasticity to generate endogenous dispersion in markups and pass-through elasticities across firms. We test the model 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 the enactment of a commercial policy in France affecting the liquidity of firms. Our results shed new light on the roots of rising markups and markup heterogeneity in recent years.

Keywords: Markups, financial frictions, firm heterogeneity, intangibles, fixed cost technology

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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 led to a growing theoretical and empirical literature studying the evolution of firm-level markups.[1]

Economists have attributed at least part of these dynamics to the increasing importance of intangible assets - such as software and IT systems - for the growth and profitability of companies. Since, as the argument goes, intangibles are scalable and exhibit synergies, firms that manage to adopt intangibles gain a competitive advantage over their rivals, breaking away from competition (Haskel and Westlake, 2018; Autor et al., 2020; Akcigit and Ates, 2019, 2020).[2]

Identifying the factors determining intangible investment is thus of primary importance to determine the root cause of rising market concentration and markups, and to understand whether or not regulatory actions are warranted. Are certain firms simply better than others at adopting intangibles, or some frictions exist providing these firms with a competitive edge over their rivals? In this paper, 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 are motivated to focus on such frictions by a large literature in finance arguing that the rise of intangibles has posed important 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 firms more susceptible to financing constraints. Despite their critical role in shaping intangible investment decisions, the consequences of financial frictions for the dynamics of intangibles and markups have largely been overlooked in the economic literature.

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 prediction using 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 novel empirical evidence that a positive and arguably exogenous shock to firm liquidity leads to a positive and significant increase in the amount of intangible assets held by firms. We then show that by increasing their intangibles, firms are able to charge significantly higher markups over marginal costs. Importantly, we show that the latter effect is mediated by financial constraints: firms with ex-ante better access to finance are able to increase their markups by more following the liquidity shock, i.e. they have a higher pass-through elasticities onto markups. We conclude that financial factors are an important and largely overlooked source of markups and pass-through heterogeneity across firms. The latter is the third and final contribution of the paper.

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

To provide guidance to 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 arise as they desire to invest in a modern, intangible technology that features a large front-loaded fixed cost in exchange for a reduction in marginal costs. Liquidity constrained firms have access to an external banking sector to finance this fixed cost investment, from which they can borrow provided that they pledge the required level of collateral. Financial frictions in the model 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]

[4]The collateral constraints reflect, for instance, bank policies or regulations common to all firms. Heterogeneous financial capability instead reflects all those factors leading to heterogeneity in the cost of borrowing or borrowing opportunities across firms, which include heterogeneity in retained earnings, bank-firm relationships, asymmetric information and/or moral hazard problems between entrepreneurs and investors (e.g. Hall and Lerner, 2010).

[5]Financial capability is the only source of heterogeneity across firms in our theoretical model. This assumption is made for analytical tractability, and is without loss of generality. All the results would go through 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 largely robust to controlling for a number of firm-level variables, including measures of firm productivity.

Financial capability is a source of competitive advantage in the model. Heterogeneous cost of borrowing induces dispersion in the shadow cost of intangibles, affecting both the extensive and intensive margin of investment in intangibles. At the extensive margin, only those firms whose financial capability is high enough find it profitable to adopt intangibles. At the intensive margin, firms with higher financial capability choose to invest relatively more, become relatively more efficient, and charge higher markups.

The source of markup variation in the model is variable elasticity of demand: firms with lower marginal costs face a lower demand elasticity and charge higher markups. Our assumptions on demand imply that heterogeneous financial capability induces dispersion not only in markups, but also in the pass-through elasticities of shocks to marginal costs into markups and prices.

We causally test the model predictions by exploiting a quasi-natural experiment in France that limited the credit terms firms could receive from their suppliers. In January 2009, France enacted a law introducing a cap of 60 days on the payment terms authorized in domestic transactions. The law acted as a positive liquidity shock to firms whose payment delays exceeded 60 days before the law was announced (Beaumont and Lenoir, 2019). We retrieve information on the average payment terms at the firm-level from our data, and we link the model to the data considering the exogenous shock to liquidity received by 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 consider a difference-in-differences identification strategy that exploits cross-sectional variation of firms in the distance from the 60 days threshold. Specifically, we test whether intangibles of firms that are further from the threshold (first difference) are higher after the change in policy relative to 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 observed distribution of the net distance from the 60 days threshold implies an increase in 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.

[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 in a positive way (as a supplier) but also in a negative way (as a buyer).

We construct firm-level markups using the cost-based approach in De Loecker and Warzynski (2012). To address standard endogeneity concerns, we consider an instrumental variable strategy where we instrument intangible investment with the exogenous liquidity shock generated by the policy reform, effectively using the results of the difference in differences analysis as our first stage estimation. We show a large and positive causal relationship between intangible investment and firm-level markups. Our results are economically significant: our baseline estimates imply that firms that increase their intangible holdings by 10% are able to 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. In the model, more financially capable firms operate on a less elastic part of the demand function, and manage to pass-through a higher portion of the shock into their markups. Our identification strategy consists in augmenting our IV specification with an interaction term between the intangible variable and a control for a firm's ex-ante intangible investment and/or financial capability. In line with the model predictions, we find that the markup pass-through of shocks to marginal costs driven by the shifts in intangibles is larger for more financially capable firms.

We have conducted a number of exercises in order to gauge the robustness of our model's results and identification strategy. First, we have replicated the main difference-in-difference analysis considering other types of investment as the main dependent variable. We found that intangibles are more sensitive to liquidity constraints than any other form of capital, in line with our prior. Then, we have run a battery of checks to rule out the concern that markups may be affected by the liquidity shock via channels other then the one of intangible investment. We showed that the liquidity shock has no direct impact on variables such as employment, revenue productivity and/or export behavior, consistent with our claim that liquidity shocks have affected markups only indirectly, through their impact on intangible investment. In doing so, we have also validated the exclusion restriction on our instrumental variable strategy. Overall, our evidence seems to suggest that confounding factors should play only a minor role in our context.

Related Literature The analysis in this paper contributes to the large debate about the sources of industry and markups dynamics in modern economies. Our evidence provides support to technology-based theories relating the observed increase in markups with the rise of intangible assets.[8] One common argument in this literature is that high markups and industry concentration stem from an efficient reallocation of market shares from low to high efficiency firms, and thus reflects efficiency gains in the economy (Autor et al., 2020). Our results however imply that, insofar as the competitive advantage of firms depends on financial frictions, the ensuing reallocation of market shares is not necessarily efficient. A second related message from our paper is that the rise of intangibles may have amplified the role of financial frictions for the aggregate economy, which may in turn have played a part in the evolution of markups and profit inequality across firms.[9]

This paper is also related to a literature emphasizing the role of financing for innovation and technological development of firms.[10] A large body of empirical work has shown that financial constraints directly affect firm-level R&D expenditures (Brown et al., 2012; Aghion et al., 2010, 2012; Hall et al., 2016). Similarly, a more recent empirical literature focusing specifically on intangible assets has shown that firms with more intangible assets use less debt, consistent with the existence of barriers to more traditional forms of financing (Bates et al., 2009; Rampini and Viswanathan, 2013; Döttling et al., 2018). We contribute to this literature by showing direct evidence of a limiting effect of financing constraints on intangibles.

In addition, our paper shows that financial frictions have implications for the dynamics of markups across heterogeneous firms. The bulk of the literature on the macroeconomic implications of financial frictions often treat markups as exogenous, thus abstracting from similar considerations.[11] 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 entry in the market. Our contribution to this literature is twofold: first, we introduce heterogeneity in credit constraints across firms and focus on the intensive margin response of investment and markups. We show that accounting for both the intensive and extensive margin effects is key to rationalize the empirical evidence. Second, we use micro-level data to provide direct causal evidence of the mechanisms.

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

[9]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).

[10]See, e.g. Hall and Lerner (2010); Brown et al. (2012); Kerr and Nanda (2015).

[11]E.g. Brunnermeier et al. (2011); Hubbard (1998); Aghion et al. (2010); Buera et al. (2011); Manova (2012); Midrigan and Xu (2014); Moll (2014); Chaney (2016); Gopinath et al. (2017)

Finally, our analysis speaks to the large literature relating markups and pass-through heterogeneity to firm-level characteristics.[12] While existing studies have focused on heterogeneity along the dimensions of productivity, size, and export status, our paper is the first to show, both theoretically and empirically, that financial factors are another, largely overlooked, source of markups and pass-through heterogeneity across firms.

Structure of the paper The paper is structured as follows. Section 2 introduces our theoretical framework along with the main testable predictions. Section 3 describes the firm-level data and main covariates. Our empirical strategy and main results are discussed in Section 4; while Section 5 shows evidence on the heterogeneous effects of financial frictions on markups. In Section 6 we explore alternative explanations for our results, and Section 7 concludes.

2 Theoretical Framework

In this section we set up a static partial equilibrium model with heterogeneous firms to investigate the equilibrium relationship between financial variables, intangible assets, and firm 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 the manufacturing sector.

2.1 Environment

Our economy is inhabited by two types of agents: workers and firms. A representative worker derives utility from differentiated varieties of consumption of the final good, and supply labor to firms. Each variety of the final good is produced by a different firm. Firms compete under monopolistic competition in the final good market. We use i to index both firms and varieties.

2.2 Demand

The focus on markup heterogeneity requires departing from the assumption of CES utility, which implies constant markups across firms. We consider a general homothetic demand system for

[12]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.

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 $D'_y < 0$. The aggregate demand shifters $Q(\boldsymbol{p}, Y)$ and $P(\boldsymbol{p}, Y)$ are taken as given by the firms, and are jointly determined from standard utility maximization constraints.[13]

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

2.3 Firms and Technology

There is free entry into the production stage, subject to an initial entry cost $f_e > 0$. Each producer i has access to two technologies to produce its own variety: *(i)* a *traditional*, constant returns technology, which uses labor as the only input in production; 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 larger the desired marginal cost reduction s_i, the larger the fixed costs the firm has to pay. 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 assets

[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.

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

that makes the firm more productive. Hereafter, we will use the terms "intangible capital" and "fixed cost technology" interchangeably. Regardless of which technology they end to adopt, firms can hire any desired amount of labor at a fixed unitary wage w, which we normalize equal to one.

The decision as to which technology to adopt depend on the relative returns to adoption. 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 the indicator function taking the value of one if the firm adopts the modern technology, i.e. if $s_i > 0$. While adopting the traditional technology does not entail fixed costs, the modern technology involves front-loading a significant fraction of the production expenses in the form of fixed costs, in exchange of lower unitary 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, are going to play a key role in the firm's choice of intangibles.

2.4 Credit-constrained Producers

Firms who want to invest in the modern technology cannot pledge future revenues nor retained earnings to pay the fixed costs. Their financing options are limited to an external banking sector, from which they can borrow provided that they pledge the required level of collateral.

Consistent with a large body of evidence in the financial literature, we assume that firms differ in their cost of raising external funds.[15] We refer to this source of heterogeneity as *financial capability*, and denote it by $\tau \in \mathbb{R}_+$, an inverse measure of the cost of external finance for a given firm. Throughout the paper, we will use *financial capability* and *financial constraints* interchangeably. We assume that the value of τ is exogenous, and is drawn upon entry by firms from a cumulative distribution function $G(\tau)$ with support over $[\underline{\tau}, \infty)$, with $\underline{\tau} > 0$.

To flexibly capture the role of τ for investment decisions, we assume that a firm whose financial capability is τ and want to make an investment of size $f(s)$ needs to ask for a loan of size $g(s, \tau) =$

[15] See, e.g. Hall and Lerner (2010); Whited and Wu (2006); Hadlock and Pierce (2010); Cloyne et al. (2018); Ottonello and Winberry (2020).

$\left(1+\frac{1}{\tau}\right) f(s)$. Only for the most financially capable firms ($\tau \rightarrow \infty$), the size of the loan corresponds to the size of the investment, i.e. $\lim_{\tau\rightarrow\infty} g(s,\tau) = f(s)$. For all other firms ($\tau \leq \infty$) the effective debt is higher than the amount of fixed costs they had to finance $g(s,\tau) > f(s)$. The wedge between the effective cost of intangibles $g(s,\tau)$ and $f(s)$ is decreasing in the financial capability of the firm. Therefore, financial capability captures all those factors that lead to heterogeneity in the (effective) cost of borrowing or in borrowing opportunities across firms, such as retained earnings, bank-firm relationships and/or asymmetric information.[16]

2.4.1 Banks

Firms can pledge a fraction $\theta \in (0,1)$ of the initial entry cost f_e as collateral.[17] The term θ is common across firms, and it captures inversely the tightness of the financial market. The lower θ, the lower the amount of collateral that firms are able to pledge, the higher 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 happens with exogenous probability $\lambda \in [0,1]$ (as in Manova, 2012). With probability $(1-\lambda)$ the firm defaults, and the bank seizes the collateral θf_e. The bank's participation constraint is thus:

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

Given perfect competition in the banking sector, 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 participation constraint.

2.5 The Firm's Problem

Given the nature of our empirical exercise, we abstract from the entry decision into the production process and focus on the problem of an incumbent firm i, with exogenous financial capability τ_i.

Let $\pi_M^R(\tau_i)$ denote ex-post profits from operating the modern technology in case of repayment,

[16] See Hall and Lerner (2010) for a review of the empirical evidence on the importance of heterogeneous constraints for the financing of intangibles.

[17] 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.

and π_T expected profits from operating the traditional technology. The firm ex-ante profits are:

$$\pi_i = \max \left\{ \underbrace{\pi_T}_{\text{Traditional technology}} \quad ; \quad \underbrace{\lambda \pi_M^R(\tau_i)}_{\text{Modern technology}} \right\}. \tag{4}$$

Since the traditional technology does not require financing ex-ante fixed costs, profits π_T do not depend on financial capability, and are thus constant across firms. The value of π_T can be found by solving the following problem:

$$\max_p (p-1) QD\left(p/P\right), \tag{5}$$

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 $y = p/P$. Because traditional firms are ex-post homogeneous, and because there is free entry into the production stage, profits of firms in this sector net of the fixed entry costs f_e are always zero. It follows that a firm will adopt the modern technology as long as $\pi_M^R(\tau_i) \geq 0$. In what follows, we characterize these profits. We later go back to the firm's optimal decision of technology adoption.

2.6 Equilibrium

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

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

$$\text{s.t.} (p-1+s) QD\left(p/P\right) \geq R(s,\tau) \tag{6}$$

$$- g(s,\tau) + \left[\lambda R(s,\tau) + (1-\lambda)\theta f_e\right] = 0. \tag{7}$$

where (6) if the firm's liquidity constraint, that guarantees that profits after debt repayment are non negative, and (7) is the bank participation constraint.

We solve the problem by first considering instances when the liquidity constraint (6) does not bind. Substituting the bank participation constraint (7) in the profit function, we obtain:

$$\max_{p,s}(p-1+s)QD\left(p/P\right)-g(s,\tau). \tag{8}$$

Unlike traditional firms, modern firms are both *ex-ante* and *ex-post* heterogeneous, due to the effect that heterogeneous financial capability τ has on the firm's effective cost of investment $g(s,\tau)$.

Intangibles and Financial Frictions Let $\rho(s)\equiv(\mu(s)-1)\,(1-s)QD\left(y(s)\right)$ denote a firm's variable profits expressed as a function of s. The first order condition associated with problem (8) governing the optimal choice of s of a firm with financial capability τ is:

$$\rho'(s)=\left(1+\frac{1}{\tau}\right)f'(s), \tag{9}$$

where $f'(s)$ denotes the marginal increase in fixed cost associated with intangible investment equal to s. Condition (9) simply states that the firm chooses the level of s that sets the marginal variable profits equal to marginal increase in financial liabilities. Ceteris paribus, firms with higher τ face a lower shadow cost of investment, and they optimally choose a higher level of s. In Appendix C, we prove that equation (9) admits a unique solution of the form $s=s(\tau)$, with $s'>0$. The latter can be synthesized in the following statement:

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

Markups and Intangibles For a given level of intangible input s, the problem in (8) is isomorphic to that of an unconstrained firm producing with constant marginal cost $(1-s)$. The optimal price is obtained as a markup over marginal cost:

$$p=\mu\left(\frac{p}{P}\right)(1-s). \tag{10}$$

Let us denote by $\Gamma\equiv-\frac{d\ln\mu(y)}{d\ln y}=\Gamma(y)$ the markup elasticity to relative price $y\equiv p/P$. Our assumptions on the demand function $D(\cdot)$ implies that $\Gamma\geq 0$.[18] By log-differentiating equation (10) and rearranging terms, we can write markups as a function of the investment choice s, and

[18]Note that in the limit case when demand is CES, markups are constant and $\Gamma=0$.

the price index P :

$$d\ln\mu(s) = \frac{\Gamma(s)}{1+\Gamma(s)}\frac{s}{1-s}d\ln s + \frac{\Gamma(s)}{1+\Gamma(s)}d\ln P. \tag{11}$$

Equation (11) shows that variation in the choice of intangible assets s induces variation of markups across firms. The larger the firm's choice of s, the higher the markup given $\frac{\Gamma(s)}{1+\Gamma(s)} > 0$. The second testable prediction follows immediately.

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

A corollary of testable predictions 1 and 2 is that, by affecting the optimal choice of intangibles, heterogeneous financial capability induces dispersion in markups across firms.

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 Γ is a key parameter governing the pass-through of shocks to marginal costs into markups and prices. From equation (11) for instance, it is easy to see that holding aggregate prices fixed, the pass-through of a shock to marginal costs into markups is simply given by: $\Phi(s)|_{\Delta P=0} = \frac{\Gamma(s)}{1+\Gamma(s)} \in (0,1)$.[19]

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

$$\frac{d\Phi(s)}{ds} > 0, \tag{12}$$

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

[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.

TESTABLE PREDICTION 3. *All else constant, the pass-through of a common shock to marginal costs into markups is larger for firms with high levels of intangible assets.*

While existing studies have focused on heterogeneity along the dimensions of productivity, size, and export status, our model thus suggests that financial factors may be another, largely overlooked, source of markups and pass-through heterogeneity across firms.

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. We argued above that a firm with financial capability τ invests whenever $\pi_M^R(\tau) \geq 0$. This means that the investment 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 in (6) 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 τ. The left hand side of (13) is an increasing function of τ, and is negative for $\tau \to 0$ given $\lambda \in (0,1)$. It follows that the solution to equation (13) is a cutoff rule that says that only the more financially efficient firms invest in the intangible technology. Linking back to the question that motivates this paper, this result implies that financial capability can provide firms with an edge over the competition, by giving firms access to a cost-reducing technology that allows them to produce more efficiently and charge higher markups over marginal costs.

The entry cutoff depends on the severity of aggregate financial market imperfections, i.e. $\tau^* = \tau^*(\lambda,\theta)$. It is easy to show that:[20]

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

Low values of either θ or λ, which corresponds to tighter financial markets, raise the entry barriers and 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 goes as

[20]See Appendix C for formal derivations.

follows. Tighter collateral constraints (e.g., lower θ) raises the entry cutoff and the average investment and markups of firms already investing in the modern technology. However, as more firms will operate the traditional technology, the measure of firms with low levels of investment and markups increases. Overall, the aggregate effect of financial frictions thus depends on whether the intensive or extensive margin prevails, and remains an empirical question.[21]

2.7 Discussion

Before turning to the data for a test of the model's predictions, we discuss some of its assumptions.

First and foremost, in our model financial capability is the only source of heterogeneity across firms. In reality, the returns on intangible investment may be heterogeneous across firms: young firms may benefit more from intangibles than older firms; similarly, larger and more productive firms may be better able to manage intangibles, getting a higher return on the investment.

It is straightforward to extend the model to include multiple sources of firm heterogeneity, most notably heterogeneous production efficiency. All the results would go through in the more general model, in a conditional sense. In the empirical analysis, we show that our results are largely robust to controlling for a number of firm-level variables, including age and measures of firm revenue productivity, which we can recover from the same production function estimation procedure that we use to construct firm-level markups (see Appendix B for more details).

A second assumption that needs to be critically appraised is that in our static framework differences in financial capability across firms are exogenously given. However, a firm's financial capability is inherently a dynamic object capturing the endogenous shadow cost of external funds to different firms (Midrigan and Xu, 2014). Our exogeneity assumption greatly simplifies the exposition and allows us to theoretically isolate the role of heterogeneous financial frictions on markups. This assumption seems nevertheless justified in our case by the fact that in our empirical analysis we rely on a quasi-experimental setup that yields exogenous variation in financial capability across firms. The latter allows us to consistently test the model predictions.

Finally, our model features a single sector in which an investment in both a traditional and a modern technology can be undertaken. However, it is widely documented that sectors differ in

[21] A quantitative assessment of the model would require extending it in general equilibrium, an exercise beyond the scope of this paper.

terms of external capital requirements, as well as in their degree of asset collateralizability (Beck, 2002; Svaleryd and Vlachos, 2005; Manova, 2012). Sectoral heterogeneity may also affect the shape of 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 must thus be interpreted as average effects.

3 Data

The empirical analysis requires three key ingredients: measures of intangible assets at the firm-level, measures of firm-level markups, and proxies for shocks to financial capability. We now discuss each of these ingredients, after a discussion of the data and the sample construction.

3.1 Data and Variable Definitions

We retrieve our panel of French manufacturing firms during the 2004-2014 period from the Orbis database provided by Bureau van Dijk. The Orbis database includes a wide array of balance sheet information, including profit accounts and financial variables.[22] We classify a firm to be in the manufacturing sector if it reports manufacturing as a primary activity, and exclude all other firms.

Sample Definition We keep all firms for which we observe the required information to compute markups and intangible investment, i.e. firms with non-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 a sample of about 38,000 unique firms observed over time. Our final dataset is representative of the official size distribution for firms in France within each two-digit industry.[23]

We work with three distinct samples of firms. In our baseline we keep all firms that enter before 2005 and exit after 2010.[24] This sample selection approach guarantees that any given firm appears

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

[23] 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.

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

both before and after the policy shock in 2008/09, thus mitigating concerns about the changing composition of the sample. We then replicate our main results on two additional samples: a fully balanced sample, which only keep those firms that are *always* present over the sample period; and the original, unbalanced 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.[25] Results are fully robust to an alternative measure of fixed cost rates obtained 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 in 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 baseline markup measure and an alternative "non-parametric" measure obtained by proxying the output elasticities by 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 variables are deflated and expressed in 2010 Euros, using industry-wide deflators that we retrieve from the STAN Industrial Database.

As expected for firm-level data, the dispersion of all these variables across firms is large. Firms in the third quartile on average are around ten times larger in sales and spend in fixed costs almost 14 times as much as firms in the first quartile, have substantially larger financial liabilities and

[25]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).

Table 1: Summary Statistics

	Obs.	Mean	St. Dev.	P25	Median	P75
Intangibles						
Fixed Costs	220,391	3,454,279	51,741,904	104,100	368,079	1,425,686
Markups						
Markup (Baseline)	220,391	1.40	0.28	1.21	1.33	1.52
Markup (Not Parametric)	220,391	1.08	0.20	0.95	1.04	1.16
Covariates						
Sales	220,391	14,123,320	239,784,080	479,141	1,466,455	5,432,000
Cash Flows	220,391	683,391	10,267,353	18,281	69,822	263,890
Loans	220,391	465,267	5,371,889	0	11,289	89,000
Current Liabilities	220,391	4,374,676	63,362,104	122,240	392,833	1,504,000

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

charge a 25% higher markup over marginal costs. These features of the data are congruent with our theoretical model where firms are (ex-post) heterogeneous in a number of 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 expenditures on fixed costs and measures of the firm's financial position, which include current liabilities, bank loans, and cash flows. All regressions include four-digit industry-year fixed effects. Columns (1)-(3) report correlations based on between regressions, which compare expenditures on fixed costs across firms. The results show that firms that spend more on fixed costs have, on average, more current liabilities and more loans, indicating that they rely relatively more on external finance. Moreover, these firms are more liquid, as it can be seen from the positive and significant coefficient on cash flows in column (3). Results are qualitatively similar when we include firm fixed effects and compare variables within-firm over time, as shown in columns (4)-(6). The evidence in Table 2 is consistent with the model assumptions that expenditure on intangibles depends in important ways on the external financial sector. It also shows that liquidity constraints are potentially important for a firm ability to invest in intangibles.

Table 3 relates measures of firm-level markups to fixed cost expenditures. The dependent variable in columns (1) and (2) is the log of firm-level "cost-based" markups. In columns (3) and (4), we consider the log of the "non-parametric" markups. Columns (1) and (3) control for industry-year fixed effects, while columns (2) and (4) use firm-level fixed effects. Results show that firms who spend more on fixed costs charge on average higher markups.

The evidence in tables 2 and 3 provides some preliminary support to the model predictions. A clear issue with OLS regressions, however, is that they could lead to biased estimates of the

Table 2: Fixed Costs and Financial Variables

	Dependent Variable: $\ln \text{Intan}_{\text{it}}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln$ Current Liabilities$_{it}$	0.848***			0.184***		
	(0.00438)			(0.00751)		
$\ln$ Loans$_{it}$		0.117***			0.00513***	
		(0.00175)			(0.000366)	
$\ln$ Cash$_{it}$			0.551***			0.0374***
			(0.00880)			(0.00199)
Obs.	198,144	198,144	177,906	198,144	198,144	177,872
R^2	0.865	0.510	0.669	0.976	0.974	0.976
Year $\times$ Industry FE	Yes	Yes	Yes	No	No	No
Firm FE	No	No	No	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, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

relationships between markups and intangibles, and/or intangibles and financial variables, if the explanatory variables are correlated with the error term. An example of such correlation is when firms optimally respond to positive demand shocks by investing more on cost-reducing technologies. The fact that correlations vary substantially in both tables across the between and within specifications suggests that our OLS estimates might indeed suffer from an omitted variable problem. In the next section, we develop an empirical strategy that deals with this potential endogeneity concerns.

Table 3: Intangibles and Markup

Dependent Variable:	$\ln \mu_{it}$ (Baseline)		$\ln \mu_{it}$ (NP)	
	(1)	(2)	(3)	(4)
$\ln \text{Intan}_{\text{it}}$	0.0129***	0.0686***	0.0104***	0.0597***
	(0.000597)	(0.00132)	(0.000546)	(0.00119)
Obs.	198,144	198,144	198,144	198,144
R^2	0.222	0.806	0.081	0.773
Year $\times$ Industry FE	Yes	No	Yes	No
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, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

4 Empirical Results

We causally identify the relationship between financial capability, intangibles and markups by exploiting a quasi-natural experiment provided by the enactment in France of a policy affecting firm liquidity. We first discuss the policy shock and the empirical setting. We then discuss our identification strategy, and finally 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 introducing a cap on the payment terms authorized in transactions contracted under the French trade code. The policy entered into force in January, 1st 2009, and was part of a larger reform aimed at the modernisation of the French economy.[26] The policy prohibited French firms to accept contractual payment terms exceeding sixty days after reception of the invoice. The enforcement of the law was strict and efficient over the French territory, as it was managed by the 7 regional Directorates of the Economic Ministry.

We follow Beaumont and Lenoir (2019) and 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 receivables over sales, multiplied by 365:

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

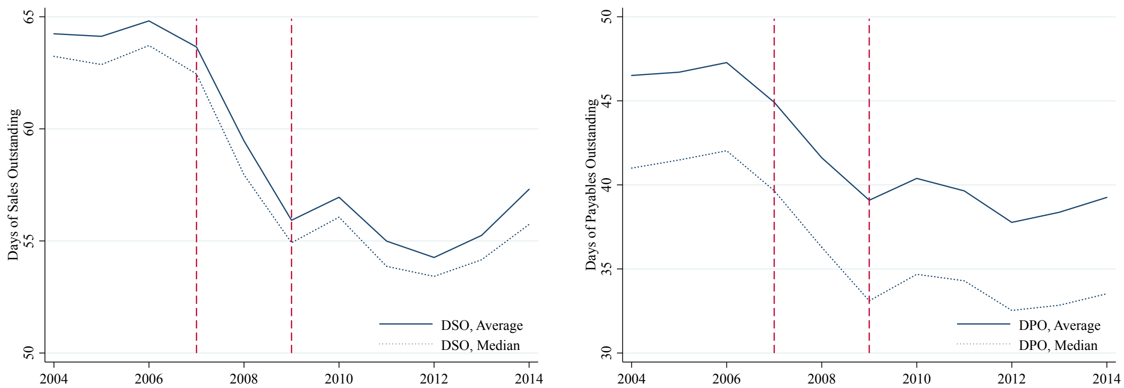
Intuitively, accounts receivables over sales represent the fraction of sales the company is still due at the end of a fiscal year. Multiplying this ratio by 365 puts the figure into a daily context. Similarly, we proxy the average time to *deliver* payments for firm i in year t as the number of days 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 is about 65.4 days for firms in our balanced sample, with a standard deviation of 43 days. On the other hand, the average DPO before 2007 is substantially lower, at about 45 days, with a standard deviation of 30 days.

[26] 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



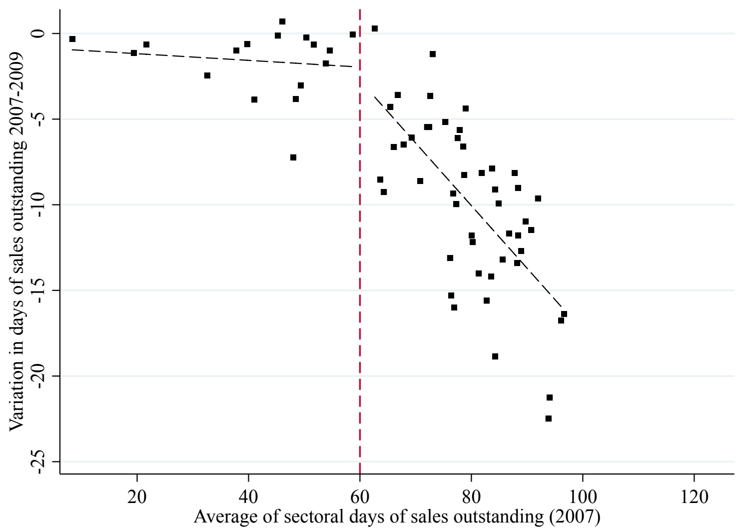
a) *DSO* **b)** *DPO*

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 1 provides a visual representation of the enactment of the policy: it shows the evolution of both the average and median days of sales outstanding of firms in our baseline sample between 2004 and 2014. The figure shows a clear drop in payment terms for the average firm, from around 65 days in 2007 to 57 in 2009 (left panel). Figure 1b shows the evolution of days of payables outstanding instead. The drop between 2007 and 2009, albeit smaller than the one on DSO, is still sharp. As in Beaumont and Lenoir (2019), we find evidence that the policy was anticipated by firms, as shown by payment periods starting to decline since 2007, one year before the law was approved. We take this anticipation effect into account in the design of our identification strategy.

Figure 2 shows the shock to DSO across different firms. The x-axis displays percentiles of the industry average DSO in 2007. For each percentile, we plot on the y-axis the mean change in DSO between 2007 and 2009, the year the policy was implemented. The sharp kink suggests that firms operating in industries where payment periods were higher than 60 days in 2007 experienced a much more significant drop in DSO than other firms in the sample. We conclude that our measure of DSO effectively picks up the effects of the 60-days rule on the variation of 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. There is no significant correlations between initial level of DSO and subsequent changes in years before 2007. This figure provides additional support to the claim that changes in DSO between 2007 and 2009 reflect the

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.

implementation of the policy.[27]

4.2 Intangibles and liquidity

We exploit the policy shock affecting the liquidity of firms to causally test the first prediction of the theoretical model, stating that more financially capable firms invest more in intangibles. In the model, financial capability is an inverse measure of the effective cost of external finance to firms. We posit that firms affected by the liquidity shock receive a positive shock to their financial capability: a firm with higher liquidity can more easily meet its short-term obligations, and hence is more likely to receive bank loans to finance intangible investment; alternatively, the firm could use the additional liquidity to partly compensate for the poor collateralizability of its intangibles.[28]

We explore the relation between financial capability and intangibles using a generalized OLS difference-in-differences (DID) specification that examines whether intangibles of treated firms (first difference) are higher after the change in policy relative to intangibles before the policy

[27] 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 the manufacturing and the wholesale sectors.

[28] See Section 6 for a thorough discussion of this point.

change (second difference).

We consider three different definitions of a treatment group. Our first and simplest definition consider a given firm i as treated if its average DSO before the policy shock was above the 60 days 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. Around 55% of the firms in our sample result as treated under this definition, and thus benefit from improved liquidity after the policy change.

The second definition considers both accounts receivable and accounts payable. It does so by accounting for the possibility that a given firm simultaneously receives a positive shock vis-á-vis its buyers (via the reduction of its average DSO), and a negative shock vis-á-vis its suppliers (due to the corresponding reduction in its DPO). For this second definition, we consider as treated only those firms that have a positive *net treatment*, thus excluding from the first set of treated firms those whose net financial position has worsened after the policy shock, i.e.:

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

Around 50% of firms in our sample experience a net positive improvement of their financial position under this definition.

Our third and preferred measure considers the net treatment as a continuous variable. This measure allows for the possibility that firms that were further away from the threshold before the policy was enacted have been treated more intensely. The treatment intensity of firm i is defined as:

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

Difference-in-differences We estimate the following equation:

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

The dependent variable is the log level 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 ($\ln T_{j,it},\ j = 1,2,3.$) and an indicator for the post-policy period. The third term is an interaction of the post-policy indicator and time-invariant firm characteristics, that include initial year (2004) sales, cash flows, loans and liabilities: this term allows for the possibility that the relationship between intangibles and these characteristics changes in the post-policy period, and is used as control in some specifications. In other specifications we include the same firm-level controls, entering either as time-invariant firm-specific characteristics, or allowed to vary over time (the fourth term in the estimating equation (20)). Finally, the term δ_{st} represent industry-time fixed effects, capturing the impact of any industry-level trend, notably demand shocks.

Note that the set of included controls allows for the possibility that a liquidity shock has different effects depending on the asset structure of the firm. This is important, as it allows us to compare the outcome of observationally similar firms over time, thus isolating the differential impact of the change in policy on intangibles.

Results are reported in Table 4 with robust standard errors clustered by firm. Columns (1)-(3), (4)-(6) and (7)-(9), show results using definition 1., 2. and 3. of the treatment group, respectively. Columns differ in the set of included controls, which are indicated in the bottom row. Our preferred estimates include firm-specific time invariant controls, and are reported in columns (1), (4) and (7). Our preferred specification is in column 7.

Estimates of the DID coefficient of interest are overall positive and statistically significant, indicating that the liquidity shock induced by the policy reform led to higher intangible investment of the treated firms. Moving across the columns from left to right shows that the estimate of the DID coefficient is largely robust across different sets of controls, and remains statistically significant at conventional levels.

The estimated effects are also economically significant. The coefficient in the baseline specification in column 7 indicates that compared to a firm in the 25th percentile of the observed distribution of $\ln T_{3,it}$ ($\ln T_{3,it}$=0), a firm in the 75th percentile ($\ln T_{3,it}$=3.41) increases its expenditure in intangibles by 4.4 (= 0.013 x 3.41) percentage points following the policy shock.

Table 4: Financial Capability and Intangibles

	Dependent Variable: ln Intan_{it}								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\text{T}_{1,it} \times \text{Post}_t$	0.053**	0.070**	0.030						
	(0.027)	(0.028)	(0.025)						
$\text{T}_{2,it} \times \text{Post}_t$				0.015***	0.017***	0.009**			
				(0.005)	(0.005)	(0.004)			
ln $\text{T}_{3,it} \times \text{Post}_t$							0.013***	0.013***	0.009**
							(0.005)	(0.005)	(0.004)
Observations	191,473	191,473	177,906	191,473	191,473	177,906	191,473	191,473	177,906
R-squared	0.916	0.916	0.944	0.916	0.916	0.944	0.916	0.916	0.944
Fixed Effect					Industry×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 days 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 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, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Robustness For the increase in intangibles to be attributable to the liquidity shock, the distance from the 60 days 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:

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

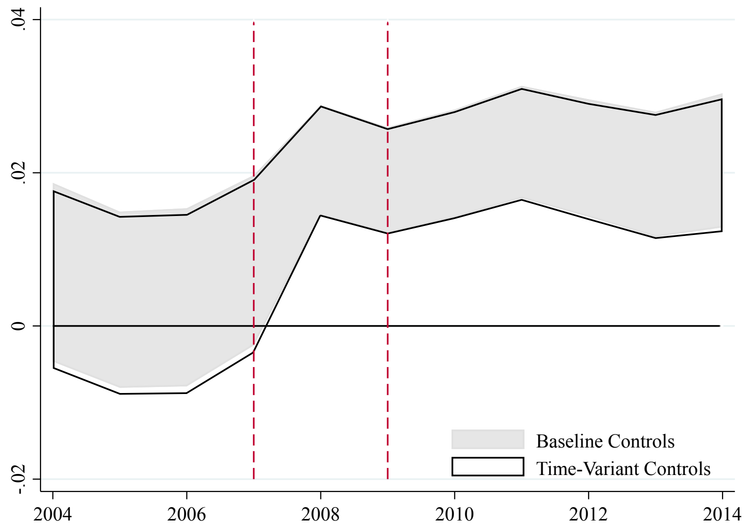
where we replace the $Post_t$ indicator in equation (20) with a vector of interactions of our treatment indicator with a set of time dummies $\pi_j,\ j \in [2004, 2014]$ that take the value of one if $t = j$.

Figure 3 displays the 95% confidence areas for the coefficients π_j, obtained from running OLS on equation (21). We consider $\ln T_{3,it}$ as our baseline definition of the treatment variable, and we consider both a specification which includes only time invariant controls X_i, and a specification where the time invariant controls are interacted with the post-policy dummy.

The area shows the average differential effect of a one percent increase in the treatment variable T_3 on the intangible expenditures of treated firms. The effect is not significantly different from zero before 2007; between 2007 and 2009 we notice a positive and significant effect, which becomes stable after 2009. The effect 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

Figure 3: Financial Capability and Intangibles - Robustness



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

the dummy treatment definition. The effects are magnified when we use the latter definition, but are robust across the different definitions of the treatment group nonetheless.

4.3 Markups, Intangibles and Financial Frictions

Having established a link between financial capability and intangibles, we now investigate the relationship between intangibles and markups. Our second model prediction says that firms who spend more on intangibles should charge higher markups over marginal costs. As firms that spend more in intangibles are those with higher financial capability in the model, this second prediction de facto relates heterogeneous financial capability to heterogeneous markup behavior, through the intangible investment channel.

The results in Table 3 provides some preliminary support to the prediction that intangibles and markups are positively related in the data. However, as we discussed above, OLS estimates may be biased by the existence of unobserved shocks, such as demand shifters, correlated with the explanatory variables.

We thus develop an instrumental variable strategy that takes into account such endogeneity concerns, while being consistent with the model 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.[29]

Table 5: Markups, Intangibles and Financial Frictions

	Dependent Variable: $\ln \mu_{it}$ (Baseline)		
	(1)	(2)	(3)
$\ln \text{Intan}_{\text{it}}$ $[\text{T}_{1,\text{it}} * \text{Post}_{\text{it}}]$	0.152***		
	(0.027)		
$\ln \text{Intan}_{\text{it}}$ $[\text{T}_{2,\text{it}} * \text{Post}_{\text{it}}]$		0.162***	
		(0.023)	
$\ln \text{Intan}_{\text{it}}$ $[\ln \text{T}_{3,\text{it}} * \text{Post}_{\text{it}}]$			0.211***
			(0.033)
Obs.	191,473	191,473	191,473
Year×Industry FE	Yes	Yes	Yes
Controls	X_i	X_i	X_i
F-Stat	26.63	37.35	22.28
Hansen J	0.40	0.42	0.15

Notes: The table shows the IV coefficients obtained by running 2SLS on equation (22). Dependent variable: *ln* μ_{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 days 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 (the log of) $T_{3,it}$, namely 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×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, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Results are reported in Table 5 with robust standard errors clustered by firm. Estimates of β are positive and statistically significant in all specifications, indicating that firms that spend more on intangibles charge significantly higher markups over marginal costs. Results from our preferred specification in column 3 say that following a 10% increase in intangibles, firms increase their price-cost margin by more than 2 percentage points.

The estimate for β is largely robust across different definitions of the treatment group. The IV regression seems to be correctly specified in light of high values of both the F-statistic on the

[29] 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.

excluded instruments, and the p-value of the Hansen J-test of overidentification. Note that the coefficients on intangibles in Table 5 are substantially larger than those obtained in equivalent OLS regressions in Table 3, indicating that the OLS estimates are indeed negatively biased.

Table 6: Robustness Checks

Treatment Variable		Coefficient	St. Error	Obs.	Hansen-J	Kleib.-Paap
$T_{1,it}$	Pre-period controls and their interactions with Post	0.159***	(0.025)	191,473	0.30	30.08
	Simultaneous controls	0.261***	(0.042)	177,906	0.90	23.72
	Controlling only for pre-period Sales	0.191***	(0.031)	198,144	0.66	27.25
	Balanced sample	0.167***	(0.038)	133,402	0.29	14.56
	Unbalanced sample	0.170***	(0.025)	234,964	0.08	26.40
	Non-Parametric Markups	0.126***	(0.027)	191,575	0.07	19.60
	Excluding crisis	0.169***	(0.031)	154,667	0.47	25.70
	Year-Sector-Region FE	0.148***	(0.024)	188,917	0.48	29.81
	Productivity control	0.151***	(0.032)	191,503	0.14	17.02
$T_{2,it}$	Pre-period controls and their interactions with Post	0.215***	(0.036)	191,473	0.22	18.92
	Simultaneous controls	0.271***	(0.039)	177,906	0.71	26.55
	Controlling only for pre-period Sales	0.302***	(0.054)	198,144	0.20	16.64
	Balanced sample	0.212***	(0.051)	133,402	0.15	9.74
	Unbalanced sample	0.234***	(0.038)	234,964	0.04	16.32
	Non-Parametric Markups	0.174***	(0.037)	191,575	0.02	13.24
	Excluding crisis	0.220***	(0.040)	154,667	0.16	19.51
	Year-Sector-Region FE	0.188***	(0.030)	188,917	0.25	19.73
	Productivity control	0.244***	(0.041)	191,503	0.10	20.49
$\ln T_{3,it}$	Pre-period controls and their interactions with Post	0.231***	(0.036)	191,473	0.26	21.87
	Simultaneous controls	0.295***	(0.039)	177,906	0.67	31.57
	Controlling only for pre-period Sales	0.304***	(0.046)	198,144	0.17	21.82
	Balanced sample	0.209***	(0.046)	133,402	0.10	11.97
	Unbalanced sample	0.235***	(0.034)	234,964	0.02	22.54
	Non-Parametric Markups	0.191***	(0.038)	191,575	0.05	14.32
	Excluding crisis	0.236***	(0.042)	154,667	0.21	20.94
	Year-Sector-Region FE	0.203***	(0.029)	188,917	0.12	23.39
	Productivity control	0.263***	(0.038)	191,503	0.13	24.82

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.

Robustness Table 6 provides a full battery of robustness checks of our baseline in Table 5. For each of the three treatment indicators, we report the main IV estimate when we alter the main specification in equation (22). In particular we perform the following changes: 1. using time-varying firm-level controls, i.e. our pre-period controls interacted with a dummy equal 1 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, where the output elasticities are 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 productive efficiency, which we measure as value added per employee.[30,31]

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

Alternative IV strategy Notwithstanding the firm-specific controls employed in the estimates, residual unobserved heterogeneity at the firm level might still affect our results. To address this concern, we consider an alternative IV strategy to estimate equation (22), where we aggregate observations at the region-industry level.

We divide our sample into clusters defined by the NACE-4 digit industries, bins of firms' size and administrative regions. We observe in fact that the enforcement of the law on the delays of payment is a duty that pertains to the seven Regional Directorates of the Economic Ministry (see Table A1 in the Appendix for the territorial partition). Due to potential differences in the efficiency of these regional directorates across different industries and firms' size classes, the legislation may have led to heterogeneous effects across different clusters.

Exploiting information on the location of each firm, 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. We then consider each cluster as treated if the average DSO of that cluster is above the 60 days threshold before 2007 and use this as instrument for intangibles. We then replicate our baseline exercise in equation (22) on this sample.

Results are in Table A2 in the Appendix. We consider different sets of fixed effects: column (1) includes year times 4-digit industry fixed effects; while column (2) includes year times 2-digit industry fixed effects. Results show that an increase in intangibles within a cluster leads to higher average markups. The estimated elasticities are smaller than those obtained in our firm-level regressions, but in the same order of magnitude (.11 vs. a range of .15-.21). The alternative IV

[30] As already discussed in Section 2.7, 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. Results would not change.

[31] 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 are available upon request.

regressions are correctly specified, as shown by the reported F- and Hansen's J-statistic.

5 Heterogeneous Pass-Through Effects

The third and last testable prediction of our theoretical model is that, all else constant, the pass-through of a common shock to marginal costs into markups is larger for firms with higher intangible holdings, or similarly for more financially capable firms.

Our identification strategy consists in augmenting our baseline specification with an interaction term between the intangible variable and a control for a firm's ex-ante intangible investment and/or financial capability, which is arguably positively correlated to their ability to operate the fixed-cost technology. The identifying assumption is that firms with higher ex-ante intangible holdings and/or financial capability initially operate on a less elastic part of the demand function, and thus, following the positive shock to intangibles, manage to pass-through a higher portion of the shock into markups.

We consider several proxies for our heterogeneous control. Our first measure is a dummy variable taking the value of one if the average share of intangibles over sales of a given firm in the years before the policy shock is above the median of all firms in the same 4-digit industry and size class. We then consider an alternative proxy of ex-ante financial capability. We follow Mulier et al. (2016) and consider a simple index of firm age, size, cash flow and leverage to proxy the likelihood that a firm faces financial constraints.[32] Our proxy of financial capability is thus a dummy variable that takes the value of one 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.

We consider the following specification:

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

Our coefficient of interest is β_2, the interaction between each firm's pre-shock financial capabil-

[32] The ASCL index assigns a value of 0 or 1 for each variable/year depending on whether a firm is scoring below or above its industry median. Firms with a higher value of ASCL are less likely to be affected by financial constraints, and thus have a higher financial capability. A similar index has been considered more recently by Cloyne et al. (2018).

ity with 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 consider an instrumental variable strategy where the first stage is a difference in difference in differences strategy that include all the interactions between the treatment variable ($\ln T_{3,it}$), the post dummy, and the financial capability dummy. We control for the same covariates already included in our 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. Results are reported in Table 7.

Table 7: Heterogeneity

	Dependent Variable: $\ln \mu_{it}$ (Baseline) (1)	(2)
$\ln \text{Intan}_{\text{it}}$ $[\ln T_{3,it} * Post_{it}]$	0.192***	0.190***
	(0.0185)	(0.0256)
$\ln \text{Intan}_{\text{it}}$ $[\ln T_{3,it} * Post_{it}]$ × Dummy Int/Sales pre above median$_{it}$	0.0299***	
	(0.00320)	
$\ln \text{Intan}_{\text{it}}$ $[\ln T_{3,it} * Post_{it}]$ × Dummy ASCL pre above median$_{it}$		0.00610**
		(0.00255)
Obs.	190,214	191,449
R2	0.264	0.296
Year × Industry FE	Yes	Yes
Controls	X_i	X_i
F-Stat	30.27	15.51
Hansen J	0.464	0.212

Notes: The table shows the IV coefficients obtained by running 2SLS on equation (23). Dependent variable: *ln* μ_{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 reports the elasticity of markups to intangibles. Consistent with our baseline estimates in Table 5, we find that expenditures on intangibles are positively and significantly correlated with firm-level markups. The second and third row reports the coefficient on the interaction term between intangibles and our financial capability proxy (intangibles over sales and ASCL, respectively). In line with the model predictions, we find that the pass-through of the shock to marginal costs induced by intangible investment into markups is larger for those firms whose ex-ante intangible holdings and/or financial capability were higher than average, 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 threshold levels.

Robustness We consider a number of robustness checks related to our heterogeneous pass-through result. We report our results in Table 8. In Columns 1 and 2 we consider our alternative, non-parametric measure of markups as the dependent variable. In Columns 3 to 6 we repeat the analysis on the fully balanced and the unbalanced sample of firms, respectively. The main results are largely confirmed across specifications.[33]

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)
$\ln \text{Intan}_{it}$ $[\ln T_{3,it} * Post_{it}]$	0.166***	0.159***	0.165***	0.199***	0.211***	0.202***
	(0.0165)	(0.0224)	(0.0218)	(0.0367)	(0.0175)	(0.0235)
$\ln \text{Intan}_{it}$ $[\ln T_{3,it} * Post_{it}]$ $\times$ Dummy Int/Sales pre above median$_{it}$	0.0264***		0.0289***		0.0303***	
	(0.00285)		(0.00375)		(0.00317)	
$\ln \text{Intan}_{it}$ $[\ln T_{3,it} * Post_{it}]$ $\times$ Dummy ASCL pre above median$_{it}$		0.00662***		0.00462		0.00993***
		(0.00230)		(0.00298)		(0.00261)
Obs.	190,214	191,449	132,745	133,382	233,029	234,931
R2	0.168	0.224	0.365	0.272	0.214	0.258
Year $\times$ Industry FE			Yes			
Controls			X_i			
F-Stat	30.27	15.51	20.22	8.162	33.95	17.35
Hansen J	0.370	0.350	0.248	0.232	0.0774	0.0106

Notes: The table shows the IV coefficients obtained by running 2SLS on equation (23). Dependent variables: columns (1)-(2), *ln* μ_{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* μ_{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$\times$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, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Taken together, our result in this section show evidence of financially-driven heterogeneity in pass-through elasticities across firms. Heterogeneity in pass-through elasticities across firms is a common finding in the empirical trade literature (e.g. Berman et al. (2012); Amiti et al. (2014)). By and large, existing studies attribute the underlying firm heterogeneity to a single variable, namely productive efficiency of firms. Our results implies that financial factors may be a second, largely overlooked source of pass-through heterogeneity across firms.

[33] 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

In this section, we critically appraise two key issues of our identification strategy. We first substantiate our claim that intangibles are more sensitive to liquidity constraints than other forms of capital investment. We then address the concern that markups may be affected by the policy shock via channels other than the one of intangible investment. In doing so, we will validate the exclusion restriction of our instrumental variable strategy in sections 4.3 and 5.

Liquidity Shock and Tangible Assets One valid concern that the reader may have is that the shock to liquidity only affects intangible investment in our model. In reality, all forms of investments may be affected by financial factors. Figure A3 in the Appendix addresses this issue. The figure replicates our exercise in figure 6, but we now consider different proxies of fixed assets as our dependent variable. While figure 6 showed an economically and statistically significant effect of the policy shock on intangibles, the same cannot be concluded when we consider tangible capital instead. This result is robust to alternative definitions of fixed assets. In the left panel of figure A3, we consider the log of total fixed assets multiplied by the user cost of capital as dependent variable; while in the right panel we define fixed assets as the log of tangible fixed assets times the user cost. Our results empirically validate claims that greater dependence on intangibles distorts firms' ability to raise external capital, most likely due to the challenges related in using this type of assets as loan collateral.[34]

What does our policy shock reflect? A second, important concern is that the intangible accumulation process is the only source of markup dynamics in our model. This assumption underlies the exclusion restriction of our instrumental variable strategy for testing the second and third model predictions, which claims that the policy shock only affects markups through its effect on intangible investment. If marginal costs respond to additional dynamic forces that are triggered by the policy shock, then our estimation will interpret such actions through an intangible accumulation lens, not the true economic process driving the decisions. One important alternative dynamic factor that our plants may consider, and that may be affected as well by the shock to payment terms, is the bargaining position of firms vis-à-vis their clients. If that is the case, the effect of the policy

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

change would be straight on markups, rather than on intangibles as we claim.

We provide supportive evidence to our identification assumption in two steps. First, we show that the policy shock seems to act as a shock to cash holdings, over and above other financial factors. Figure A4 shows the effect of the policy shock 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 π_j, obtained from running OLS on the following equation

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

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

We then run the same exercise on several strategic variables of the firm: markups, revenue productivity, employment and export behavior. Figure A5 shows the 99% confidence areas for the coefficients π_j, obtained from running OLS on equation (24) with these dependent variables. As it can be seen, the policy shock does not seem to have a direct effect on any of these firm-level variables, with the exception of markups, where the effect is statistically significant, but not economically significant given the size of the coefficient. We interpret figures A4 and A5 as evidence in favor of our main assumption, namely that the policy shock acted as a shock to firm liquidity, and only affected markups indirectly through the effect on investment in intangibles. While we cannot fully rule out that other factors played a role in determining the main results, due to limitations in data availability, the evidence presented in this section seems to suggest that these confounding factors should play only a minor role in our context.

7 Conclusions

We discuss in this paper the link between financial factors, investment in intangibles, and firm-level markups. We propose a theoretical explanation of the relationship between these variables based on 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 entry into investment, and at the intensive margin, distorting the level of investment of individual firms. We are able to find causal evidence of the intensive margin effect of heterogeneous financial frictions on intangibles and markups, exploiting a quasi natural experiment induced by the enactment of a commercial policy in France in 2009, whereby payments periods for a certain group of firms have been substantially reduced, increasing their liquidity holdings.

Two policy implications follow from our results. First, the documented markup trends in modern economies can be the result of the increasing importance of intangible assets. In turn, the marked difference in markup trends between US and European firms registered in the last decade can be partly explained by the higher level of intangible capital investment by US firms. Second, access to finance is a critical component in the ability of firms to invest in intangible capital. Heterogeneous access to finance may lead to sub-optimal investments in intangibles, high markup dispersion, and high misallocation of capital in the economy.

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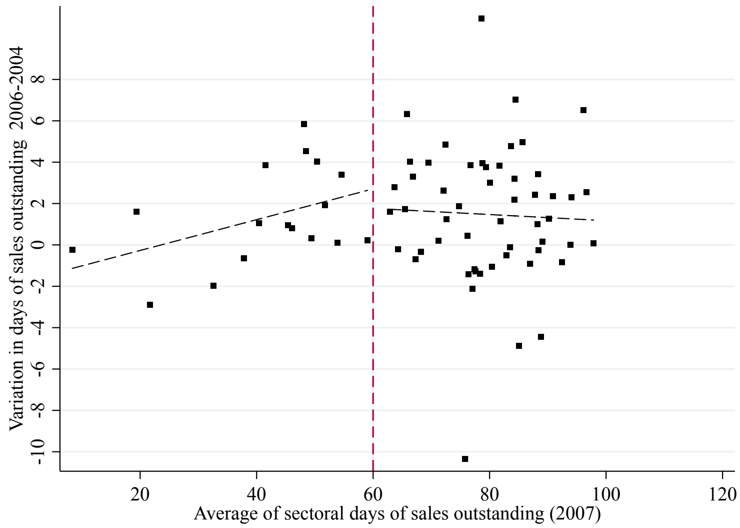
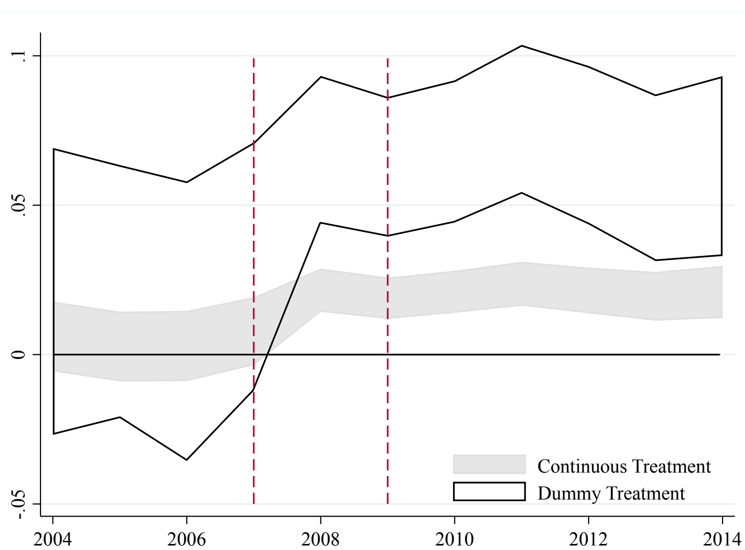
A Additional Figures and Tables

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



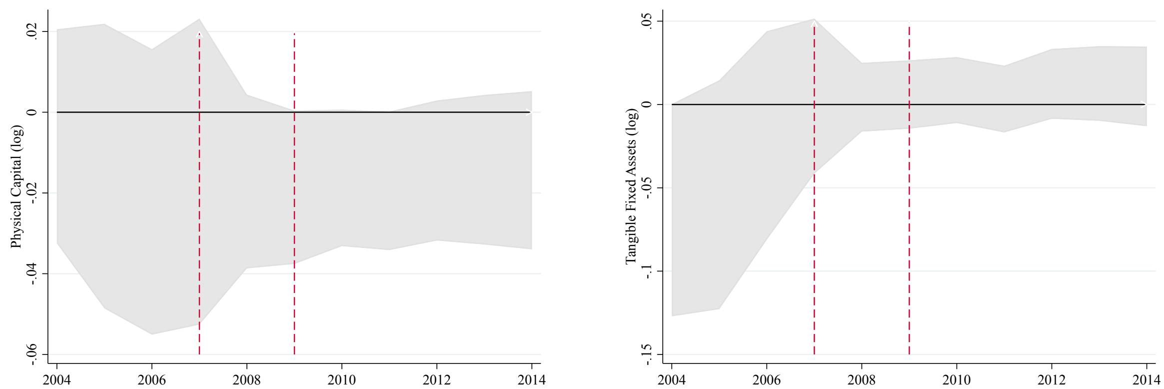
Notes: This graph displays the difference in days of sales outstanding between 2004 and 2006 as a function of the average DSO in 2004 for each NACE-4 digit industry. DSO is computed as the firm-level ratio of accounts receivable over sales multiplied by 365. The data set is split in 100 percentiles along 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 π_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 $\ln T_{3,it}$.

Figure A3: Liquidity Shock and Tangible (Fixed) Assets



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

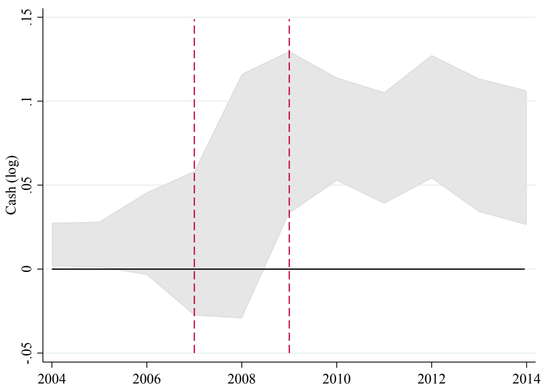
Notes: The graph displays the coefficients π_j, with 99% confidence intervals, obtained from estimating equation $\ln Y_{it} = \sum_{j=2004}^{2014} \pi_j \cdot \ln T_{3,ij} + X_i' \lambda + \delta_{st} + \alpha + \epsilon_{it}$ using OLS. The variable Y is given by (log) physical capital expenditures, 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 sales, loans, cash flows, cash and non-current liabilities measured in the first year of the sample (2004).

Table A1: Regional enforcement of the policy

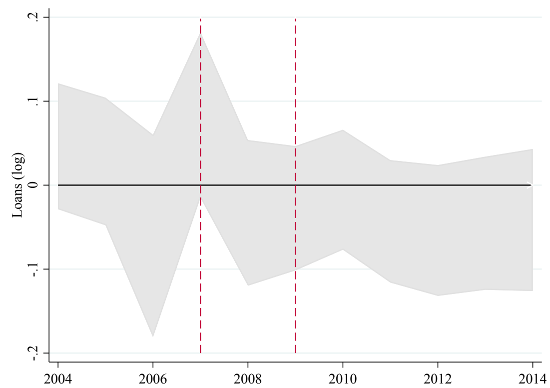
Regional directorate	Region
Direction régionale du Nord	Nord - Pas-de-Calais Picardie
Direction régionale de Lorraine	Champagne-Ardenne Lorraine Alsace
Direction régionale de Rhône-Alpes	Bourgogne Franche-Comté Rhône-Alpes Auvergne
Direction régionale de Provence-Alpes-Côte d'Azur	Languedoc-Roussillon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

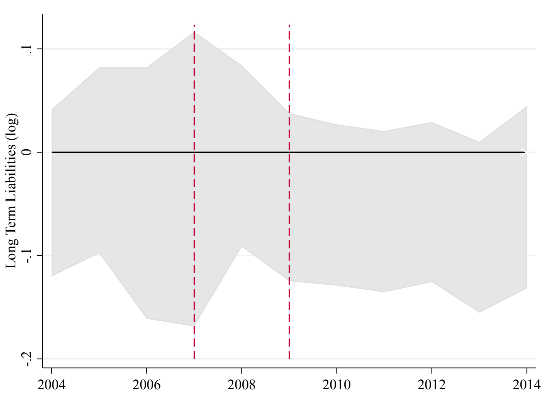
Figure A4: Liquidity Shock and Financial Variables



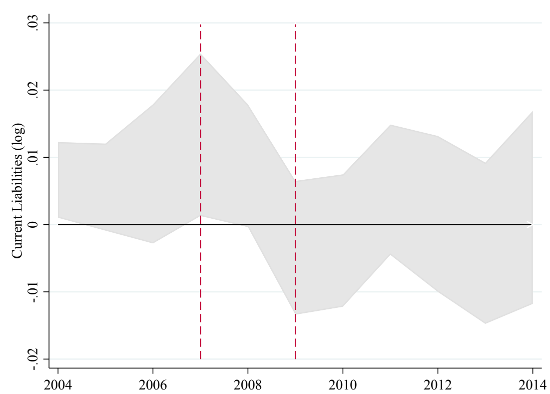
a) *Cash*



b) *Loans*



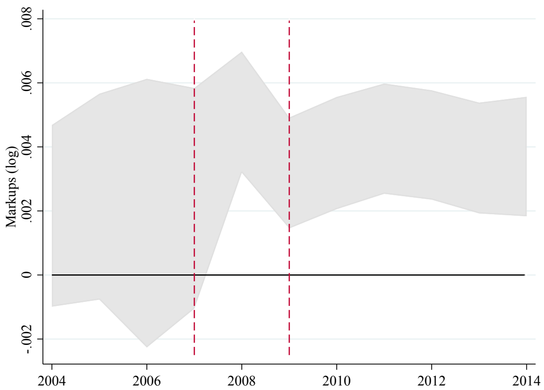
c) *Non current liabilities*



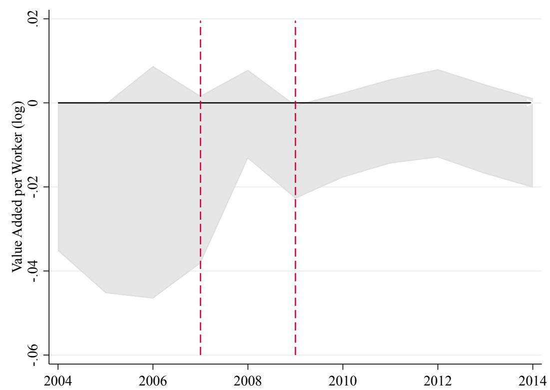
d) *Current liabilities*

Notes: The graph displays the coefficients π_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 sales, loans, cash flows, cash and non-current liabilities measured in the first year of the sample (2004).

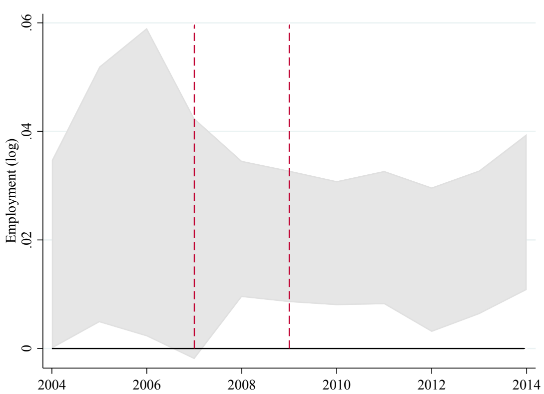
Figure A5: Liquidity Shock and Real Variables



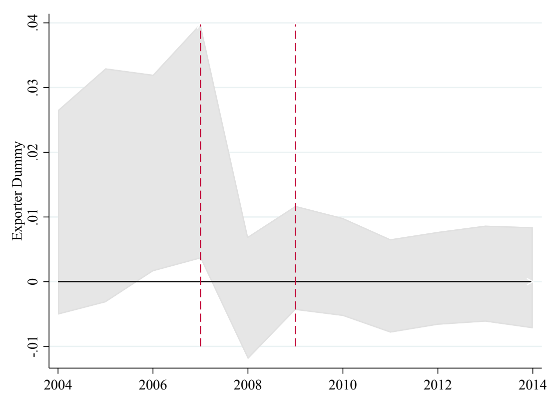
a) *Markups*



b) *Revenue Productivity*



c) *Employment*



d) *Export Behavior*

Notes: The graph displays the coefficients π_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) baseline markups, (log) revenue productivity, (log) employment and a dummy equal to 1 if the firm is an exporter, respectively. The set of controls X_i include sales, loans, cash flows, cash and non-current liabilities measured in the first year of the sample (2004).

Table A2: Baseline regression with regional interaction

	Dependent Variable: $\ln \mu_{it}$ (Baseline)	
	(1)	(2)
$\ln \text{Intan}_{\text{it}} \left[DSO_{industry} \times Post_t\right]$	0.110***	0.114***
	(0.0323)	(0.0154)
Obs.	191,473	191,575
R2	0.470	0.424
Year $\times$ Industry 4 digits FE	Yes	No
Year $\times$ Industry 2 digits FE	No	Yes
Region FE	Yes	
Controls	X_i	
Hansen J	0.722	0.145
F-Stat	11.45	36.12

Notes: The table shows the IV coefficients obtained by running 2SLS on equation (22). Dependent variable: *ln* μ_{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 days threshold before 2007. All specifications include Regional Directorates fixed effects, column (1) includes Year×Industry 4 digits fixed effects, while column (2) includes Year×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, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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 the procedure for estimating the production function, 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 ω_{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 ω_{it} and ϕ_{it} are observed by the firm when choosing inputs. The term ϵ_{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 ω_{it} and implictly 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 consider the more general case where firms have different levels of production efficiencies, even conditional on their intangibles holdings.

Neither ω_{it} nor ϕ_{it} nor ϵ_{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 ϕ_{it} to depend both on the fixed cost expenditures and on the unobserved productivity term ω_{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.

As it is well-known in the literature, estimation of (26) requires dealing with several biases. Not only we have to deal with the unobserved term ω but because we only observe nominal measures of inputs and output, we also have to deal with well-known price biases in 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:

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

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 ω_{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 β_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 ω_{it} and ϕ_{it}. We estimate (28) using the procedure in Wooldridge (2009). The identifying restrictions are that the innovation to the TFP process are 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. What we can identify is 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:

$$\mu_{it} = \frac{\theta^v_{it}}{\alpha^v_{it}},$$

where $\theta^v_{it} = dq_{it}/dv_{it}$ is the output elasticity of the variable input and $\alpha^v_{it} \equiv \frac{E^v_{it}}{R_{it}}$ is the share of expenditures on variable inputs E^v_{it} 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:[35]

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

Markups are then computed as:

$$\hat{\mu}_{it} = \hat{\theta^v_{it}} \left(\frac{E^v_{it}}{R_{it}}\right)^{-1}.$$

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

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

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

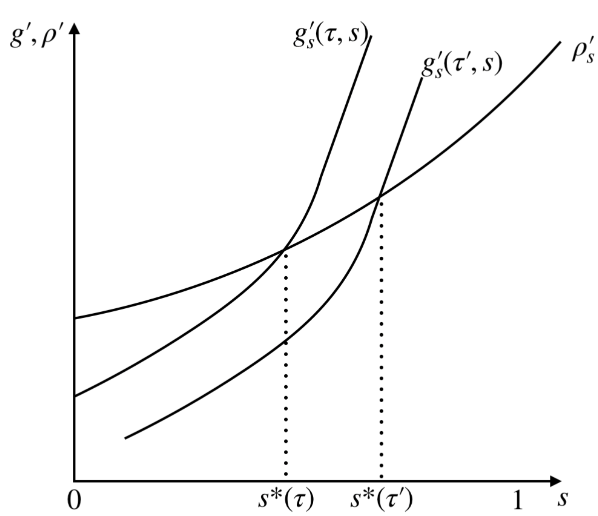
$$\theta^v_{it} = \frac{dq_{it}}{dv_{it}} = \beta_v + 2\beta_{vv}v_{it} + \beta_{kv}k_{it}$$

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 τ, with $\tau' > \tau$.

Figure C1: Equilibrium value of s



Notes: The graph shows dynamic of s, g', and ρ', for two different values of τ, 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 τ :

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

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 $\mu'_s > 0$

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

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.