Markups, Intangible Capital, and Heterogeneous Financial Frictions*

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Abstract

We estimate the effect of liquidity constraints on investment in intangible capital and how this leads to differences in markups across firms. We exploit variation in liquidity shocks across firms induced by a policy reform as a quasi-natural experiment to establish causality. We show that: 1) following a positive liquidity shock, firms increase their investment in intangible assets, 2) by holding more intangibles, firms can charge higher markups over marginal costs. Our results show that financial constraints may have contributed to markup inequality across firms through their effect on intangible investment, with implications for the efficiency of recent macroeconomic trends.

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1 Introduction

Over the past decades, many advanced economies have seen a surge in intangible capital as a share of investment (Corrado et al., 2009), and a concurrent increase in markups and markup inequality (De Loecker et al., 2020), even with some heterogeneity across countries (Corrado et al., 2018; De Loecker and Eeckhout, 2018; Díez et al., 2021). These secular trends have been extensively debated and researched.[1] A popular narrative is that since the intangible capital deepening has reallocated market shares towards the most productive firms, the resulting rise in markups reflects efficiency gains for the economy (Autor et al., 2020; Van Reenen, 2018). Yet despite the academic interest and the far-reaching policy implications, there is still little consensus about what drives these trends and what they represent for the economy overall, in part due to the data challenges related to measuring markups and and drawing credibly causal inference.[2]

The fact that intangibles and markups have grown at different speeds in different countries suggests that institutional barriers might affect their evolution. Financing constraints are likely part of these barriers. Intangibles' intrinsic characteristics such as information problems and lack of collateral value restrict a firm's ability to access to external finance, forcing the firm to rely on internal funds to finance investment.[3] In turn, a lack of liquidity thwarts profitable investment opportunities of firms, affecting their productivity and ability to charge markups over marginal costs. The presence of financing constraints may thus have implications for the efficiency of aggregate markups: insofar as intangible investment reflects heterogeneity in the shadow cost of capital across firms, the ensuing markup dynamics is not necessarily efficient.

This paper makes progress on these issues by showing that financial factors, through the intangible channel, are a largely overlooked source of differences in markups across firms. Specifically, we address three related research questions. First, is the intangible investment of firms significantly affected by the availability of internal liquidity? Second, do differences in intangible investment across firms translate into differences in markups? Third, can financial factors explain, at least in part, differences in trends in intangibles and markups across countries?

We use data on French manufacturing firms between 2004 and 2014 for our main empirical exercise. The focus on France is empirically motivated. First, we have access to

[1]See, e.g. Van Reenen (2018); De Loecker et al. (2020); De Loecker and Eeckhout (2018); Syverson (2019); Barkai (2020); Crouzet and Eberly (2018, 2019); Akcigit and Ates (2020); Eggertsson et al. (2021); Andrews et al. (2016).

[2]On measurement issues for markups, see, e.g. Covarrubias et al. (2020) and Syverson (2019).

[3]On the role of finance for intangible investment and R&D, see, e.g., Hall (2010); Bates et al. (2009); Falato et al. (2020); Döttling et al. (2018); Lim et al. (2020); De Ridder (2019); Sandström (2020).

balance-sheet variables for a large and representative sample of firms, which allows us to construct measures of intangible investment and markups following state-of-the-art techniques in the empirical macroeconomics literature. Second, we can exploit quasi-experimental variation in liquidity shocks across firms generated by a policy reform in France in 2009 to provide novel causal evidence of the relationships between liquidity, intangibles, and markups at the firm level.

We start by showing evidence of a causal effect of liquidity on intangible investment. Access to finance has long been recognized as a key driver of investment, and a large empirical literature has investigated the investment implications of financing constraints, typically focusing on traditional forms of (tangible) capital. As for any type of investment, the ideal experiment for identifying the role of liquidity constraints is to give firms additional cash exogenously, i.e., a change that conveys no new information about the profitability of investment, and observe whether or not they use it to invest (i.e., buy intangibles). Because experiments of this kind are typically hard to come by, the corporate finance literature has had to rely on alternative econometric techniques to estimate the investment demand equation, with varying degrees of success.[4]

To overcome the identification problem, we exploit variation in firm-level liquidity induced by a policy reform in France as a quasi-natural experiment and a difference-in-differences identification strategy. A significant advantage of our data is that they span a time, amid the financial crisis of 2008-09, when France underwent a series of reforms to improve firms' financing. Notably, the French government passed a law in 2009 introducing a cap of 60 days on the term of the credit that firms could receive from their suppliers in domestic transactions. As regional Directorates of the Ministry of the Economy strictly enforced the law, the latter translated into a positive (negative) liquidity shock to suppliers (buyers) whose (re)payment delays had previously exceeded 60 days (Beaumont and Lenoir, 2019).

Our difference-in-differences identification strategy exploits firms' cross-sectional variation in the net exposure to the policy, testing whether firms further from the no-exposure threshold of 60 days (first difference) change investment trajectories by more after the policy change vs. before (second difference). As the initial distance from the threshold might not be exogenous to firms' future performance and investment profitability, we include firm fixed effects in all our specifications, as well as several firm-specific time-varying controls. We further test for pre-trends to rule out that the treated and control group were on different investment trajectories before the shock. Our results show a large and positive impact of liquidity shocks on the intangible holdings of firms. In particular, the

[4]See, e.g., Hall and Lerner (2010) for a survey of the literature.

evidence shows that moving a firm from the 25$^{\text{th}}$ to the 75$^{\text{th}}$ percentile of the distribution of the net distance from the threshold (i.e., a more positive liquidity shock) leads to a 4.4 percentage points increase in intangible expenditures.

We consider a battery of robustness checks to test the validity of our results. We incorporate different sets of firm-level time-varying controls in the baseline specifications, and consider alternative definitions of the treatment variable and measures of intangible investment. We show that our results are robust to all these different specifications, which validates our causal interpretation of the effect of liquidity on intangible investment.

Next, we investigate the relationship between intangible investment and firm-level markups. To guide the empirical analysis and shed light on the mechanisms, we develop a theory of production with heterogeneous firms, intangible assets, and imperfect financial markets. Dispersion of markups across firms arises due to the variable elasticity of demand: the more productive firms (who charge lower prices) face lower demand elasticity and charge a higher markup over marginal costs. A firm's productivity have exogenous and endogenous sources: While companies are born with some idiosyncratic productivity, firms may also lower their marginal costs through investment in a modern, intangible technology featuring a high upfront cost in exchange for a proportional reduction in variable costs. The intangible capital is thus modeled as a cost-reducing technology allowing firms to gain a competitive advantage over their rivals. In turn, the presence of liquidity constraints induce dispersion in the internal cost of intangible capital, such that ceteris paribus, firms with greater liquidity invest relatively more, become more productive, and charge higher markups.

The simple model highlights how unobserved factors may bias standard OLS estimates of the effect of intangibles on markups. To establish causality, it is essential to isolate changes in intangibles due to factors unrelated to productivity. We leverage our quasi-experimental setting and consider an instrumental variable strategy where the firm-specific liquidity shock from the reform is used as an instrument for intangible investment. Consistent with the predictions of the theory, we find that firms that invest more in intangibles charge significantly higher markups over marginal costs. The results are statistically and economically significant: the baseline estimates imply that firms that increase their intangible expenditures by 10% can increase their price-cost margins by more than 2 percentage points. These estimates are broadly robust to changing the set of controls in regressions and using alternative measures of markups.

Our principal measure of firm-level markups is constructed using the cost-based approach pioneered by De Loecker and Warzynski (2012). This approach infers markups from the ratio of the output elasticity of a variable input and its revenue share. Markups are thus straightforward to estimate, given estimates of the output elasticity of the variable input that can be obtained from production function estimation. However, the standard approach to estimating production functions ignores the role of intangibles in production, potentially leading to biases in the estimates of output elasticities and markups (Compnet, 2020). One methodological contribution of this paper is to adapt standard techniques in the literature to our setup by writing firm-level productivity as a function of intangible investment, in line with the assumptions of our theoretical model.

Our primary evidence shows that financial constraints can explain part of the diverging trajectories in intangible investment and markups across firms *within* a country. In the last part of the paper, we entertain the possibility that the same forces may explain the heterogeneous trends in intangibles and markups *across* countries. Using ORBIS firm-level data, we construct firm-level datasets for the U.S., Italy, and Spain similar to the French dataset. Leveraging cross-country heterogeneity in the key variables of interest, we show that across industries and countries, investment in intangibles strongly co-moves with aggregate liquidity, and trends in intangibles are positively related to trends in markups, these relationships holding even controlling for several set of fixed effects. We conclude that institutional factors, and especially financial constraints, may be part of the reason why countries and firms have grown unequal in terms of intangible investment and markups. Therefore, improving countries' financial development could help firms and countries realize their growth opportunities and mitigate inefficiencies and misallocation.

Our paper contributes to a growing literature studying trends in markups and intangibles in advanced economies. De Loecker et al. (2020) use U.S. Compustat firms to estimate markups using the cost-based approach in Hall (1988) and De Loecker and Warzynski (2012). They show evidence that aggregate markups in the U.S. have risen dramatically between 1980 and 2015. Similar conclusions have been reached by Hall (2018) and Autor et al. (2020) using different data and approaches. Díez et al. (2021) use firm-level data on private and listed firms from 20 countries to look at the evolution of market power around the world between 2000 and 2015, finding that markups have been on the rise in many advanced economies.

Crouzet and Eberly (2019) provide evidence that over the past decades, the accumulation of intangible capital across U.S. industries has occurred hand-in-hand with the increase in market power. Theories that provide a unified explanation of rising markups and intangible capital deepening include Aghion et al. (2019) and De Ridder (2020). One critical argument in this literature, both empirical and theoretical, is that the rise in industry concentration and markups stem from a reallocation of market shares from low- to high-markup firms, and may thus reflect efficiency gains in the economy.

However, understanding the sources of rising concentration is critical for understanding the extent to which the markups dynamics is efficient or not, and possible policy implications (Crouzet and Eberly, 2019). The evidence in this paper offers new perspectives around this issue. In particular, while the fact that intangible investment increases a firm price-cost margin supports a technology-based explanation of rising markups and is consistent with "winners take all" dynamics, we argue that the allocation of intangibles across firms is not necessarily reflective of the firms' productivity insofar as it is driven by heterogeneous financial access across firms. The rise in aggregate markups may be not be efficient after all, even if related to intangible capital deepening.

While the relationship between investment in intangibles and internal liquidity was already well-understood (Bates et al., 2009; Hall, 2010; Falato et al., 2020; Lim et al., 2020; De Ridder, 2019; Rampini and Viswanathan, 2013), to the best of our knowledge, our study is the first to provide causal evidence in a well-identified setting. In this sense, our evidence also deepens our understanding of the drivers of investment in intangible capital.

Lastly, we contribute to the empirical literature identifying the causal effect of financial constraints on investment. This literature, which dates back to Fazzari et al. (1988) and typically focuses on "traditional" forms of (tangible) capital, has used an array of methodologies providing mixed evidence on the effect of financial constraints (Kaplan and Zingales, 1997; Almeida et al., 2004; Brown et al., 2012; Bond and Meghir, 1994).[5] Our main contribution is to use a novel empirical strategy to show direct evidence of an adverse effect of liquidity constraints on less traditional forms of capital investment.

The paper is organized as follows. Section 2 presents our data and variable construction. Section 3 reviews the econometric challenges of relating dispersion in liquidity to intangible investment, and shows the evidence relating liquidity shocks and intangible investment. Section 4 discusses what happens to markups following an exogenous shock to intangible investment, and interprets the results through the lenses of a theoretical model of intangibles, markups, and financial frictions. Section 5 shows some cross-country evidence and discusses the aggregate implication of our results. Section 6 concludes and discusses directions for future research.

2 The Data

We take our panel of French manufacturing firms, 2004-2014, from the ORBIS database provided by Bureau van Dijk. The ORBIS database includes a wide array of balance sheet

[5] See Hubbard (1998) and Schiantarelli (1996) for comprehensive surveys of this literature.

items, including profit accounts and financial variables, providing information, either direct or indirect, on a firm's expenses on intangible assets, markups, and liquidity.[6]

We classify a firm as a manufacturing firm if it reports manufacturing as its primary activity and exclude all other firms. We retain firms for which we observe the required information to compute markups and intangible investment, i.e., firms with no missing values for sales, profits, employment, output, assets, and materials. We restrict the analysis to those firms that report the number of employees for more than 50% of the years in the sample, ending up with about 38,000 unique firms observed over time. Our final dataset is representative of the official size distribution of French firms within each two-digit industry.[7]

Finally, we restrict our baseline sample to firms that enter before 2005 and exit after 2010.[8] This sample selection guarantees that any given firm appears both before and after the policy shock in 2008/09, mitigating concerns about changing sample composition. In robustness exercises, we show that all our results replicate on the original, unbalanced sample.

2.1 Variable Construction

Intangible Capital Generally, the term intangible capital refers to the sum of knowledge-based capital and organization capital (Peters and Taylor, 2017). Knowledge-based capital includes a firm's expenditures to develop knowledge, patents, or software, while organizational capital includes advertising to build customer capital, human capital, and distribution systems. Existing theories relating intangibles to markups span both knowledge-based assets (e.g., De Ridder, 2020) and organization-based ones (e.g., Crouzet and Eberly, 2018, Morlacco and Zeke, 2021).

In ORBIS data, a measure of intangible assets is directly reported as part of a firm's balance sheet. We take this variable as our baseline measure of intangibles.[9] One caveat is that the accounting standards mandate that balance sheets report a firm's intangible assets only insofar as they are acquired externally. Our direct measure of an intangible asset may thus underestimate the value of intangibles for those firms whose intangibles

[6] Gopinath, Kalemli-Özcan, Karabarbounis, and Villegas-Sanchez (2017) have used similar ORBIS data for Spain to study the effect of size-dependent financial frictions for aggregate productivity.

[7] 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.

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

[9] The original ORBIS variable is IFASS, formally defined as "all intangible assets such as formation expenses, research expenses, goodwill, development expenses and all other expenses with a long-term effect".

are (primarily) generated internally.

We then construct a second measure of intangibles as total company's expenses unrelated to production costs. This measure is based on the following accounting definition for intangible expenses:

$$\underbrace{\text{Intangible expenses + other operating expenses}}_{\text{Operating Expenses}} = \text{revenues - variable costs - operating profits}$$

where "other operating expenses" include rents, inventory costs, marketing, and insurance. Since all the variables on the right-hand side are observed, we can proxy intangible expenses as operating expenses, as long as other operating expenses vary proportionally with intangibles.[10]

In robustness exercises, we consider a third measure of intangibles based on a time-varying measure of fixed costs constructed as the difference between the marginal cost markup and the profit rate, as in De Ridder (2020).

Markups Markups are not directly observed from balance sheet data due to a lack of data on marginal costs and prices. We follow the cost-based approach in De Loecker and Warzynski (2012), which infers price-cost margins from the gap between output elasticity, which needs to be estimated along with the production function coefficients, and the revenue share of a variable input expenditure, which is observed in balance-sheet data.

One potential issue with this approach to estimating markups is it typically ignores the role of intangibles in production, potentially leading to biases in the estimates of output elasticities and markups (CompNet, 2020). We address this concern by adapting the existing techniques to our setup, and we describe our approach in Appendix C. Consistent with theories of markup-enhancing intangibles, which we review in Section 4, we specify firm-level TFP as a function of a firm's intangible investment. We then estimate the inputs' output elasticity using the procedure proposed by Ackerberg et al. (2015). We will show results using both this markup measure and an alternative "non-parametric" measure obtained by substituting the output elasticities with the average input cost share at the four-digit industry-year level.

While the De Loecker and Warzynski (2012)'s approach to estimating markups has been frequently used, several studies have recently raised skepticism about its validity. The main critiques of this procedure relate to the bias that arises using revenue rather than

[10]This proxy for intangible investment is strongly correlated with the balance-sheet measure of intangible assets: The correlation coefficient from an OLS regression of intangible assets on intangible expenses that include firm and industry-year fixed effects is 0.12, significant at the 1% level.

Table 1: Summary Statistics

	Obs.	Mean	St. Dev.	P25	Median	P75
Intangibles						
Intagible Assets	217,840	112,114	351,677	0	13,722	78,199
Intangible Expenses	215,658	1,552,645	3,827,498	87,553	309,771	1,193,630
Markups						
Markup (Baseline)	217,858	1.337	0.789	0.800	1.100	1.667
Markup (Not Parametric)	217,857	1.666	0.868	1.156	1.427	1.873
Covariates						
Current Liabilities	215,663	2,106,510	5,742,269	122,233	377,319	1,380,237
Cash Holdings	210,793	373,982	796,460	21,422	90,390	333,000
Accounts Payable	214,833	960,845	2,601,045	35,008	148,641	649,388
Accounts Receivable	217,001	1,238,724	3,186,125	45,357	232,914	896,842

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

quantity data to estimate the production function (Bond, Hashemi, Kaplan, and Zoch, 2021), and from misspecification of the first stage (Doraszelski and Jaumandreu, 2021). Recently, De Ridder, Grassi, Morzenti, et al. (2021) have argued that while the *level* of revenue-based markups is affected by bias, their *dispersion* across firms and correlation with other measures of firm-level profitability are not. Furthermore, they show that the specification of the first stage has minor effects on the estimates of the production function parameters, providing even more support to our approach.

2.2 Summary Statistics and Preliminary Evidence

Table 1 presents summary statistics for measures of intangibles, markups, and firm's liquidity in our baseline sample.[11] As is to be expected for firm-level data, the dispersion of all these variables is substantial. Firms in the third quartile on average spend 14 times on intangibles as firms in the first quartile, and charge a more than twice higher markup over marginal costs.

The table also shows substantial variation in firm-level liquidity, as measured by current liabilities, cash holdings, and trade credit, namely of debt (credit) to (from) suppliers. The label 'Accounts Payable' indicates the total amount of debt the company owes to suppliers at the end of the fiscal year, a measure of how much the company relies on short-term credit from suppliers. Similarly, 'Accounts Receivable' records the total amount of sales the company is still owed by buyers at the end of the fiscal year. The amount of trade credit ranges on average around 15% of turnover for the median firm, a figure that resonates with the fact that trade credit is one of the most important source of short-term

[11] All the variables are expressed in 2010 euros, using industry-wide deflators from the STAN Industrial Database.

finance for firms (Cunat, 2007).

Tables A.1 and A.2 in the Appendix show preliminary evidence that liquidity, intangibles, and markups are related to each other. Table A.1 shows simple OLS correlations of firm-level intangible capital with firm-level measures of liquidity. All regressions include firm and year fixed effects. The results show that the firms that own more intangible assets have more liquid assets, on average. This finding is consistent with ample empirical evidence showing that the rise of intangibles has led firms to optimally hold more cash or use more trade credit in order to preserve financial flexibility (Falato et al., 2020; Bates et al., 2009).

Table A.2 shows results of OLS regressions of firm-level markups on intangibles. All columns include controls for firm-level liquidity, as measured by current liabilities and cash holdings. We report results using both the baseline markup measure and the "non-parametric" measure (NP) obtained by using industry-level cost shares as a proxy for output elasticities. All regressions include firm and year fixed effects. Results show that firms that spend more on intangibles also charge higher markups over marginal costs.

3 Liquidity and Intangibles

A large finance and macroeconomics literature studies the relation between firm-level investment and cash measures to test for the presence and importance of financing constraints.[12] One lesson from this literature is that the evidence of a positive intangibles-cash flow sensitivity like the one in Table A.1 is insufficient to draw causal inference: A firm's current cash position correlates to future investment opportunities, leading to a link between investment and liquidity even in the absence of financial market imperfections.

The ideal experiment for identifying the effects of liquidity constraints is to give firms additional cash exogenously, i.e., a change that conveys no new information about the profitability of investment, and observe whether or not they use it to buy capital.[13] In a perfect capital market, a firm should not increase investment when investment opportunities do not change. A finding that intangibles are sensitive to cash flow shocks that are not signals of future demand increases would reject the hypothesis that the cost of external funds is the same as the cost of internal funds, and show evidence of liquidity

[12]See, e.g., Bond and Van Reenen (2007) for a review of this literature.

[13]Because experiments of this kind are hard to come by, researchers have used alternative econometric techniques to sidestep the econometric challenge, with varying degree of success. One common approach is to examine the differences in cash-investment correlations between groups of firms hypothesized to have different dependence on internal finance. See, e.g., Fazzari et al. (1988); Hoshi et al. (1991). See Kaplan and Zingales (1997) for a critique of their approach and Fazzari et al. (2000) for a response to the critique.

constraints.

In Appendix B, we illustrate this key source of endogeneity in the context of a theoretical model with heterogeneous firms, intangible capital, and liquidity constraints à la Melitz (2003). The model shows that, in the absence of financial market imperfections, differences in firm-level intangibles across firms should only depend on the idiosyncratic firm-level productivity, capturing the shadow value of investment akin to the marginal q in standard Q-theories of investment. On the contrary, when financial markets are imperfect and liquidity constraints are binding, firms with higher liquidity are expected to invest more. The theory also shows that because liquidity depends both on exogenous financial factors and idiosyncratic productivity, to identify the presence of liquidity constraints one must isolate changes in liquidity due to factors unrelated to productivity, captured by the term θ in the model.

Our data and setting are particularly suited for testing for liquidity constraints. We exploit quasi-exogenous variation in liquidity shocks across heterogeneous firms induced by a policy reform in France that directly affected firm cash-in-hand. We interpret the policy shock as a shock to θ in the model. In the next paragraphs, we review the policy reform and describe the empirical strategy in details.

3.1 Quasi-Experimental Setting

In August 2008, the French government approved a reform setting a cap on the payment terms authorized in transactions under the French trade code. The policy - sent into force on January 1st, 2009 - was part of a broader reform to modernize the French economy.[14] It prohibited French firms from accepting contractual payment terms exceeding sixty days after receipt of the invoice. Enforcement was strict and efficient throughout France, as it was managed by the seven regional Directorates of the Ministry of the Economy.

Following Beaumont and Lenoir (2019), we proxy the average time to *receive* payments for firm i in year t as the number of days of sales outstanding (DSO, henceforth), which we construct as the ratio of accounts receivable over sales, multiplied by 365:[15]

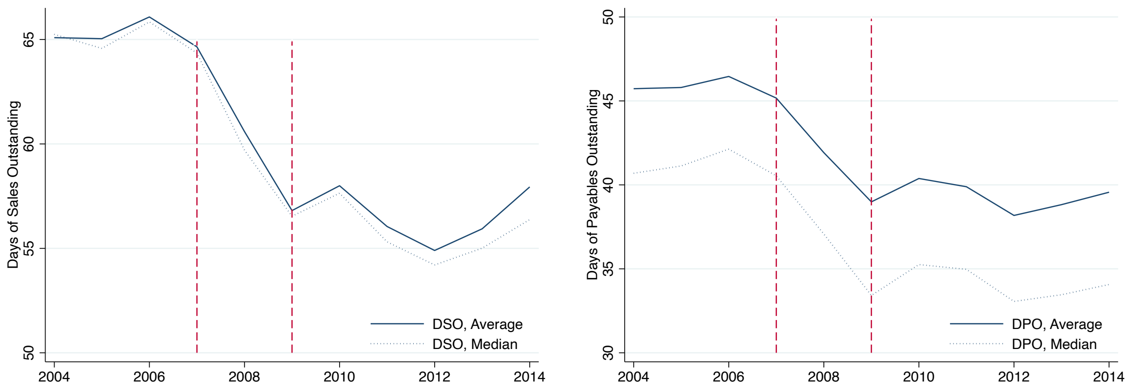
$$\text{DSO}_{it} = \frac{\text{Accounts receivable}_{it}}{\text{Sales}_{it}} \times 365. \tag{1}$$

Similarly, we proxy the average time to *deliver* payments by firm i in year t as the number of days of payable outstanding (DPO, henceforth), which we construct as the

[14] 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.

[15] Intuitively, accounts receivable over sales represent the fraction of sales the company is still owed at the end of a fiscal year. Multiplying this ratio by 365 gives a daily rate.

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



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

Notes: Figures 1a and 1b show the evolution of both the average and median days of sales outstanding of firms (DSO) and of days of payable outstanding (DPO), respectively, between 2004 and 2014 in our baseline sample.

ratio of accounts payable over sales, multiplied by 365:

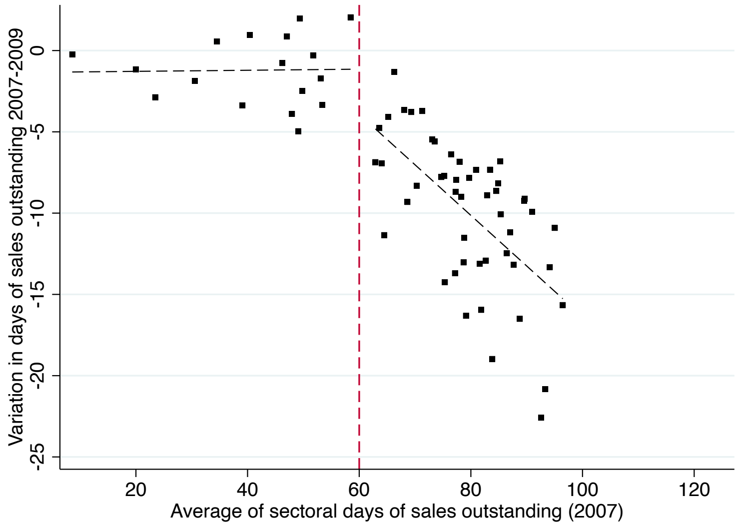
$$\text{DPO}_{it} = \frac{\text{Accounts payable}_{it}}{\text{Sales}_{it}} \times 365. \tag{2}$$

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

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

Figure 2 shows the shock to DSO across different firms. The x-axis displays percentiles of the industry average DSO in 2007. The y-axis gives the mean change in DSO between 2007 and 2009 (the year of implementation) for each percentile. The sharp kink suggests that industries where payment periods were longer than 60 days in 2007 experienced a much more significant DSO drop than other industries, and hence a relatively large positive liquidity shock. In addition, we show in Figure A.1 in the Appendix the placebo exercise of considering changes in DSO between any two years before the policy shock,

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.

i.e., between 2004 and 2006. Before 2007, there is no significant correlation between the initial level of DSO and subsequent changes. We conclude that our DSO measure effectively picks up the effect of the 60-day rule on the variation in payment periods.

3.2 Difference-in-differences

We estimate the direct effect of liquidity on intangible investment using a difference-in-differences (DiD) identification strategy. The standard DiD approach uses the onset of a treatment to identify the average treatment effect on the treated. In our setting, this means comparing changes in intangible asset holdings before and after the policy change for treated versus untreated firms. The critical assumption is that the difference between the treated and untreated groups in how much their intangible assets would change over time if both groups were untreated would be equal to zero (parallel trends assumption).

Two distinct definitions of the treatment group are considered. The first definition considers a firm i as treated if its net debt position vs. other firms has improved following the implementation of the policy. We construct the treatment variable as:

$$T_{1,i} = \mathbb{1} \cdot \left[\max\{DSO_{pre,i} - 60, 0\} - \max\{DPO_{pre,i} - 60, 0\} > 0 \right], \tag{3}$$

where $DSO_{pre,i}$ and $DPO_{pre,i}$ denote the average firm DSO and DPO before the policy shock. According to this definition, a firm is considered as treated if its payment terms from buyers improved more than its payment terms to suppliers worsened.[16] This definition treats around 50% of sample firms.

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

$$T_{2,i} = \max\left\{\max\{DSO_{pre,i} - 60, 0\} - \max\{DPO_{pre,i} - 60, 0\}, 0\right\} \tag{4}$$

In regression analysis, we will take the log of this second treatment variable.

One crucial concern is that the assignment of firms to treatment and control group is non-random and may be correlated to a firm's future liquidity and performance, violating the parallel trends assumption. Appendix Figure A.2 mitigates, in part, this concern by showing no significant differences between treatment and control groups in the trends in intangible capital before the policy shock; trends start to diverge evidently after 2009 instead. To further isolate the differential impact of the policy change on intangible investment, all regression specifications below include firm fixed effects and controls for the firm's average liquidity before and after the policy shock.

We estimate the following equation:

$$\ln Y_{it} = \alpha + \beta \cdot Post_t \times T_{j,it} + Post_t \times X_i' \gamma + c_i + \delta_t + \epsilon_{it}, \quad j = 1, 2. \tag{5}$$

The dependent variable $Y_{it} = \left\{\text{Intan}_{it}; \text{IntanExp}_{it}\right\}$ includes measures of intangibles of firm i at time t. The second term on the right-hand side is the DiD term of interest: an interaction of the treatment variable ($T_{j,it}$, $j \in \{1, 2\}$) with an indicator for the post-reform period, starting with 2009, as the reform has been implemented since January of that year. The third term interacts the post-indicator with measures of firm liquidity, namely initial-year (2004) current liabilities and cash holdings. Finally, all specifications include firm (c_i) and year (δ_t) fixed effects.

Results are reported in Table 2 with standard errors clustered by firm. The estimates of the DiD coefficient of interest are positive and significant, indicating that the positive

[16] Consider a firm being paid within 80 days on average before the policy change, i.e. $DSO_{pre} = 80$. Assume that the same firm was paying its suppliers within 70 days ($DPO_{pre} = 70$). After the implementation of the policy, this firm would see its net liquidity position improve, as she would be receiving payments from its customers 20 days earlier (80-60), while she would need to pay its suppliers 10 days earlier (70-60).

Table 2: Financial Capability and Intangibles

	(1)	(2)	(3)	(4)
Estimation:	DiD OLS			
Dep. Variable:	ln Intan$_{it}$		ln IntanExp$_{it}$	
$T_{1,it} \times Post_t$	0.053		0.021	
	(0.013)		(0.007)	
ln $(1+T_{2,it}) \times Post_t$		0.013		0.006
		(0.004)		(0.002)
Obs.	152,372	151,732	212,662	211,640
R^2	0.902	0.902	0.962	0.962
Fixed Effects:	Firm; Year			

Notes: The table shows DiD coefficients obtained by running OLS on equation (5). The dependent variable in columns (1)-(2) is the (the log of) firm-level intangible assets from balance sheet; it is total firm expenditure on fixed costs in columns (3) and (4). $T_{1,it}$ is the treatment variable defined in equation (3), and is a dummy = 1 if the firm received a net positive liquidity shock following the policy reform. $T_{2,it}$ is defined in equation (4), and treats the treatment as a continuous variable. $Post_t$ 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 firm and year fixed effects. In all regressions we control for pre-period (2004) firm cash holdings and current liabilities interacted with $Post_t$. Standard errors are in parentheses and clustered at the firm level.

liquidity shock led to higher intangible investment in treated firms. Moving from left to right columns shows that the estimate of the DiD coefficient is robust to different definitions of the treatment variable, and different measures of intangible assets. The effects estimated are also economically significant. The coefficient in column (2), which considers the continuous treatment, indicates that compared to a firm in the 25th percentile of the observed distribution of $T_{2,it}$ ($T_{2,it}$=0), a firm in the 75th percentile ($T_{2,it}$=3.41) increases its intangible assets by 4.4 (= 0.013 x 3.41) percentage points following the policy change.

3.3 Robustness

Figure A.3 in Appendix reports a battery of 48 robustness checks on our estimate of β. In particular, we show how β changes as we: (i) change the set of controls, including controls for firm sales and TFPR and considering both time invariant controls interacted with the Post dummy and time-varying controls; (ii) consider alternative definitions of the intangible variable, including the two baseline measures and a third measure based on fixed cost expenditures constructed as in De Ridder (2020); (iii) considering the two alternative definitions of treatment; (iv) excluding the years of the financial crisis, and (v) running the main specifications on the original unbalanced sample of firms. The Figure shows that: (i) all estimates of β are positive, with only three exceptions where the coefficient is not statistically significant, and (ii) the great majority of them are within the range of the estimates shown in Table 2.

3.4 Industry Heterogeneity

We now show that the link between liquidity and intangibles is especially sizable in industries that are: (1) more intangible-intensive and (2) more exposed to liquidity constraints. The first exercise aims to show that our estimates are not due to measurement error in our measures of intangible capital; the second exercise confirms instead that our experimental setting does indeed capture a financial shock to firms.

To measure industry-level intangible intensity, we follow Demmou et al. (2020) and consider U.S. Compustat firm-level data, where detailed measures of intangible spending and its components are available. The underlying assumption is that in a frictionless world, intangible intensity is akin to a sectoral technological characteristic that does not vary across countries. Being the U.S. a relatively frictionless market, the intangible assets level comes close to optimal levels. We select the years in the pre-reform period (2004-2007) and construct two measures of industry-level intangible intensity. The first measure is taken as ratio of Sales and General Administrative Expenses (SG&A) over sales. The second measure aims to capture knowledge-based capital intensity and is constructed as the ratio of R&D over sales. The latter measure is consistent with our theoretical model that considers intangibles are a productivity-enhancing technology. We aggregate firm-level measures to 4-digit industry medians for empirical analysis. Appendix Tables A.3 summarizes intangible intensity by 2-digit sector along with its R&D component.

We then construct measures of industry-level financial dependence to capture heterogeneity in liquidity constraints. Following Rajan and Zingales (1998), we construct a measure of pre-reform External Financing Dependence (EFD) as the difference between each firm's capital expenditures and cash flows with respect to the same capital expenditures, in the years between 2004 and 2007. A high value of this indicator indicates that capital expenditures are not covered entirely by the firm's cash-flow. Hence these firms are more dependent on external finance for their investment, or more liquidity constrained. We aggregate firm-level measures to 4-digit industry medians for empirical analysis. Appendix Table A.4 reports EFD by 2-digit sector. Both tables show substantial heterogeneity in these two measures across industries.

Table 3: Liquidity and Intangibles - Heterogeneity

	(1)	(2)	(3)	(5)	(6)	(7)
Estimation:	DDD OLS					
Dep. Variable:	ln Intan$_{it}$			ln IntanExp$_{it}$		
Panel (a): Intangible Intensity						
T$_{1,it}$×Post$_t$	0.053	-0.000	0.030	0.021	0.007	0.008
	(0.013)	(0.017)	(0.014)	(0.007)	(0.009)	(0.007)
T$_{1,it}$×Post$_t$×SG&A Int$_{s,t0}$		0.215			0.056	
		(0.045)			(0.019)	
T$_{1,it}$×Post$_t$×R&D Int$_{s,t0}$			0.930			0.544
			(0.211)			(0.096)
Obs.	152,372	152,372	152,372	212,662	212,662	212,662
R^2	0.902	0.902	0.962	0.962	0.962	0.962
Panel (b): External Financing Dependence						
T$_{1,it}$×Post$_t$	0.053	0.084	-0.024	0.021	0.041	0.016
	(0.013)	(0.018)	(0.034)	(0.007)	(0.010)	(0.020)
T$_{1,it}$×Post$_t$×EFD(Cap)$_{s,t0}$		0.025			0.018	
		(0.012)			(0.008)	
T$_{1,it}$×Post$_t$×EFD(Fixed Assets)$_{s,t0}$			0.152			0.010
			(0.063)			(0.036)
Obs.	152,372	152,372	152,372	212,662	212,520	212,662
R^2	0.902	0.902	0.962	0.962	0.962	0.962
Fixed Effects:	Firm; Year					

Notes: The table shows the coefficients obtained by running OLS on equation (6). The dependent variable in columns (1)-(2) is the (the log of) firm-level intangible assets from balance sheet; it is total firm expenditure on fixed costs in columns (3) and (4). The Overall Intangible intensity is measured as firm-level Sales and General Administrative Expenses (SG&A) over total sales. The R&D intensity is measured as firm-level R&D expenses over total sales. Both measures are retrieved from U.S. Compustat firm-level measures and aggregated at the 4-digit NACE sector level by taking the median-firm intangible intensity ratio of each sector. EFD(Cap) is defined as in Rajan and Zingales (1998) as (Capital Expenditures (CE) - Cash Flows (CF))/CE. An alternative measure is based on expenditures on total fixed assets. Firm-level estimates are aggregated at the 4-digit NACE sector level by taking the median-firm ratio of each sector. Standard concordance tables from www.eurostat.com are used to convert 6-digits NAICS industries in Compustat to 4-digit NACE industries in ORBIS. Source: authors' calculations on Compustat data.

We test for heterogeneous effects by modifying regression (5) to also include an interaction between industry intensity (ψ_s), treatment, and the post dummy:

$$\ln Y_{it} = \alpha + \beta_1 \cdot Post_t \times T_{j,it} + \beta_2 \cdot Post_t \times T_{j,it} \times \psi_{s,t0} + Post_t \times \tilde{X}_i'\gamma + c_i + \delta_t + \epsilon_{it}, \quad j = 1, 2, \tag{6}$$

where $\psi_{s,t0}$ is industry intensity measure – either intangible or EFD intensity – before the policy reform, while $\tilde{X_{i(t)}}$ now includes both liquidity controls and the industry intensity measure.[17] The coefficient of interest is now β_2, the coefficient on the triple interaction term. It represents the differential effect of the policy on treated firms in industries with either high intangible-intensity or high EFD.

Table 3 shows results. Panel (a) considers the heterogeneous effects by industry-level

[17]Note that firm and year fixed effects subsume the individual term $T_{j,i}$, $\psi_{s,t0}$ and $Post_t$, respectively.

intangible intensity. The triple interaction coefficient is positive and significant, showing that the effect of the liquidity shock is stronger in industries with high intangible intensity, and in particular high knowledge-intensive (R&D-intensive) industries. Panel (b) shows results when we consider heterogeneous effects by industry-level external finance dependence. The triple interaction coefficient is again positive and significant, showing that the effect of the liquidity shock is stronger in industries that are more dependent on external finance, or where liquidity constraints are expected to be more binding.

4 Markups, Intangibles and Financial Frictions

Having showed that intangible spending is subject to significant financing constraints, this section moves on to investigate whether intangibles affect the ability of a firm to charge a markup over marginal costs.

The idea that intangibles can lead to competitive advantage and higher markups is well-understood theoretically. Recent contributions in the macroeconomics literature include De Ridder (2020) and Morlacco and Zeke (2021). In De Ridder (2020), heterogeneous firms invest in a technology (intangible capital) that allows them to reduce variable costs proportionally. Idiosyncratic differences in the ability to deploy intangibles will lead to different levels of investment and cost reductions. By gaining a cost advantage, the best firms can charge a higher markup over marginal costs. Morlacco and Zeke (2021) provide a model of a duopolistic industry where heterogeneous firms advertise strategically to accumulate customer capital. In the model, customers are a form of (intangible) capital to the firms: Ceteris paribus, a higher customer base allows the firm to charge higher prices and markups.

In Appendix B, we provide a formal theoretical model with heterogeneous firms, variable markups, and financial frictions to illustrate this key markup-enhancing property of intangibles and motivate our empirical strategy below. The source of markup dispersion in the model is a variable elasticity of demand: firms who charge lower prices face lower demand elasticity and charge a higher markup over marginal costs (Arkolakis et al., 2018). Firm-level differences in marginal costs have both exogenous and endogenous sources. While companies are born with some idiosyncratic productivity, a cost advantage may also arise endogenously through investment in a modern, intangible technology.[18] An exogenous shift in intangible investment, like that generated by the liquidity shock, may thus lead to (heterogeneous) changes in markups through its effect on the marginal cost distribution.

[18] In this sense, our approach to modelling intangibles follow the one in De Ridder (2020).

One lesson from the theory is that a positive correlation between intangibles and markups, like that shown in Table A.2, may be spurious in the presence of confounding factors. In the model, more productive firms (i.e., firm with a better draw of idiosyncratic productivity) invest more and charge higher markups. The existence of such unobserved idiosyncratic factors leads to an endogeneity bias in simple OLS regressions. Therefore, to estimate the causal effect of intangibles on markups, one must isolate changes in intangibles that originate from factors unrelated to idiosyncratic firm-level shocks. To that end, this section considers an instrumental variable strategy that uses the policy shock as an instrument for intangible expenditure.

4.1 Results

We consider the following specification:

$$\ln \mu_{it} = \alpha + \beta \ln Y_{it} + Post_t \times X_i' \gamma + c_i + \delta_t + \epsilon_{it} \tag{7}$$

where $\ln \mu_{it}$ denotes the log markup of firm i at time t, and the remaining terms are as above, with $Y_{it} = \{\text{Intan}_{it}; \text{IntanExp}_{it}\}$. We run 2SLS regressions on (7), instrumenting intangibles with the DiD setup described above, thus with the treatment times post interaction, after partialling out firm and year fixed effects and liquidity controls $X_{i(t)}$.

Results are reported in Table 4 with robust standard errors clustered by firm. The estimates of β are positive and statistically significant in all specifications, indicating that firms that spend more on intangibles charge significantly higher markups. The instrument is strong, with a first stage F-statistic greater than 37 in all specifications, well exceeding the Stock and Yogo (2005) rule-of-thumb cutoff of 10.

Our preferred specification in column 1 suggests that after a 10% increase in intangible capital, a firm's price-cost margin widens by almost 3 pp. Results are largely robust to different definitions of the treatment group and measure of intangible capital (column (2)-(4)). We note that the coefficients on intangibles in Table 4 are substantially higher than those obtained in equivalent OLS regressions in Table A.2, indicating that the OLS estimates are indeed biased.

4.2 Robustness

We report in Figure A.4 in the Appendix a full battery of robustness checks on our estimates of β. In particular, we show how β changes as we: (i) change the set of controls, including controls for firm sales and revenue productivity and considering both time in-

Table 4: Markups, Intangibles and Liquidity

	(1)	(2)	(3)	(4)
Estimation:		2SLS		
Dep. Variable:		$\ln \mu_{it}$		
$\ln$ Intan$_{it}$[T$_{1,it}\times$ Post $_t$]	0.292			
	(0.100)			
$\ln$ Intan$_{it}$[$\ln(1+T_{2,it})\times$Post$_t$]		0.319		
		(0.125)		
$\ln$ IntanExp$_{it}$ [T$_{1,it}\times$Post$_t$]			0.818	
			(0.307)	
$\ln$ IntanExp$_{it}$[$\ln(1+T_{2,it})\times$Post$_t$]				0.714
				(0.272)
Obs.	152,372	151,732	212,662	211,640
Fixed Effects:		Firm; Year		
CD F-Stat	58.25	41.73	37.93	39.76

Notes: The table shows the IV coefficients obtained by running 2SLS on equation (7). Dependent variable: *Markups$_{it}$* indicates firm-level markups following De Loecker and Warzynski (2012). Different rows correspond to different definitions of the treatment group in the first stage and different measures of intangibles. *Intangibles$_{it}$* indicates (the log) firm-level intangible assets from balance sheet, while *Intangibles SGA$_{it}$* indicates (the log) firm-level intangible assets measured as total firm expenditure on fixed costs. We instrument them with the interaction of two different treatments with a post-change in policy variable. In column 1 and 3, the treatment $T_{1,it}$ is a dummy = 1 if the firm-level average DSO before the policy shock was above the 60-day threshold. In column 2 and 4, 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. All specifications include firm and year fixed effects. All variables are deflated and expressed in 2010 Euros. All specifications include firm and year fixed effects. In all regressions we control for pre-period (2004) firm cash flows and current liabilities interacted with *Post$_t$*. Kleibergen-Paap Wald F statistics are reported at the bottom of the table. Standard errors are in parentheses and clustered at the firm level.

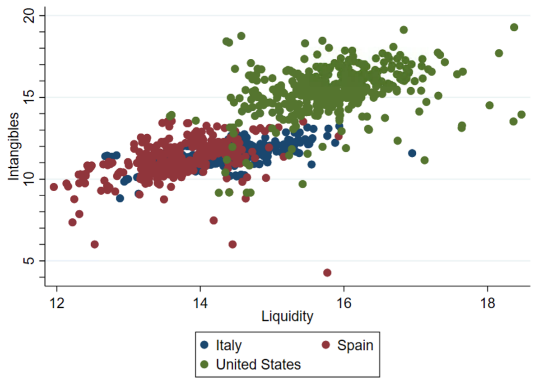
variant controls interacted with the Post dummy and time-varying controls; (ii) consider alternative definitions of the markup variable, as explained in section 2; (iii) consider the two alternative definitions of treatment; (iv) exclude the years of the financial crisis, and (v) run the main specifications on the original unbalanced sample of firms. The figure shows that: (i) all estimates of β are positive and statistically significant, and (ii) the great majority are between 0.2 and 0.5, with our preferred estimate largely within all confidence intervals. We also report the F-stat for all specifications, which shows a strong instrument in all specifications.

5 Macroeconomics Implications

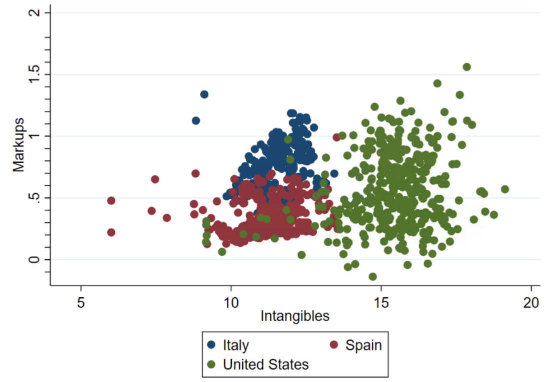
Our main evidence shows that financial constraints can explain part of the variation in intangible investment and markups across firms *within* a country. We now entertain the possibility that the same forces may explain the differences in trends in intangibles and markups *across* countries.

We do so by leveraging the ORBIS database to build three representative firm-level

Figure 3: Cross-country heterogeneity



a) *Liquidity and Intangibles*



b) *Intangibles and Markups*

Notes: Figures 3a and 3b show scatter plots of industry-country measures of intangibles and liquidity (Figure 3a) and intangibles and markups (Figure 3b). Intangibles and markups are constructed using the same methodologies as in our French sample, described in Section 2. Liquidity is measured as 'current liabilities' at the firm level. All variables are aggregated at the 4-digit industry level using sample weights.

samples for the U.S., Italy and Spain.[19] Using the same procedures as for our main sample of French firms, we construct measures of liquidity, intangibles, and markups at the firm level, which we then aggregate at the country-(4-digit) industry level using sample weights constructed from official Eurostat statistics.

Figure 3 shows a correlation between liquidity and intangibles, and intangibles and markups, across countries and industries. Consistent with our main firm-level results, we show that even at the aggregate level, industries where firms hold more liquidity invest more in intangibles, and feature higher markups over marginal costs. Figure A.5 in the Appendix shows that this remains the case after controlling for country and industry fixed effects. While anecdotal, the cross-country evidence in this Section, together with the evidence in the rest of the paper, suggests that institutional factors, and especially financial constraints, may be part of the reason why countries and firms have grown unequal in terms of intangible investment and markups.

These results have important policy implications. Investment is often a leading target of public policy interventions, for instance through monetary policy and low interest rates. Our results suggest that policy interventions targeting the liquidity of firms could improve the capital allocation choices made by firms, with implications for aggregate markups and efficiency.

Moreover, different European countries have fared differently in terms of aggregate productivity growth and productivity dispersion, and understanding the sources of these

[19]Details on data construction available on request.

differences in productivity is a primary concern for policymakers.[20] Our cross-country evidence suggests that financial factors, through the intangible investment channel, are an essential and largely overlooked source of differences in markups and productivity between firms and, potentially, countries.

6 Concluding Remarks

We discuss the link between financial (liquidity) constraints, investment in intangibles, and firm-level markups. We do so in the context of a policy reform in France in 2009, generating quasi-experimental variation in liquidity shocks across firms. Our analysis extends existing empirical studies linking trends in markups to trends in intangibles because: (i) we provide causal evidence of the relationship between intangibles and markups at the firm level; (ii) we point at one source of dispersion in intangible holdings across firms, namely the availability of internal funds. Our first set of results provide empirical support to those theories relating a firm's markups and market power to its intangible investment, and it is consistent with the narrative that documented trends in markups in modern economies may stem from the increasing importance of intangible assets. Our second set of results enlarges a literature trying to pinpoint the sources of competitive advantage of firms investing in intangibles, by showing that the success of the "superstar" firms may be as much due to their financial conditions rather than their intrinsic productivity.

We highlight two directions for future research. First, our difference-in-differences research design, exploiting differences in liquidity shocks on the investment of otherwise similar firms, can inform us on the differential effect of liquidity on investment but not on its absolute importance. Future work can embed financial frictions in a macro-model of intangibles to quantify the importance of liquidity constraints on aggregate level of investment and aggregate markups. Second, future research could delve more deeply into understanding the extent to which differences in financial conditions across countries may provide an explanation for the observed cross-country differences in intangible investment and markups, an important open policy question.

[20] See, e.g., the 2020 CompNet Firms Productivity Report (CompNet, 2020)

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A Additional Figures and Tables

Table A.1: Intangibles and Liquidity

	(1)	(2)	(3)	(4)	(5)	(6)
Estimation:	OLS					
Dependent Variable:	ln $Intan_{it}$			ln $IntanExp_{it}$		
Current $Liabilities_{it}$	0.223			0.224		
	(0.0109)			(0.00819)		
Cash $Holdings_{it}$		0.00298			0.0348	
		(0.00402)			(0.00310)	
Accounts $Payable_{it}$			0.126			0.214
			(0.00924)			(0.00678)
Observations	155,792	147,875	155,479	217,920	205,862	217,428
R-squared	0.903	0.903	0.902	0.963	0.963	0.964
Fixed Effects:	Firm; Year					

Notes: OLS estimations. The dependent variable *ln* $Intan_{it}$ indicates the log of firm-level intangible assets, as measured in firm-level balance-sheets. By taking logs, we exclude those firms with zero levels of intangible fixed capital. The dependent variable *ln* $IntanExp_{it}$ indicates the log of Intangible Operating Expenses, measured as revenues minus production costs, operaing profits and depreciation. *Current* $Liabilities_{it}$, *Cash* $Holdings_{it}$, and *Debt to* $Suppliers_{it}$ are (the log of) firm-level current liquidity. All variables are deflated and expressed in 2010 Euros. All specifications include year and firm FE. Standard errors clustered at the firm level are in parentheses.

Table A.2: Intangibles and Markup

	(1)	(2)	(3)	(4)
Estimation:	OLS			
Dependent Variable:	ln μ_{it} (Baseline)		ln μ_{it} (NP)	
ln $Intan_{it}$	0.00348		0.00408	
	(0.00195)		(0.00234)	
ln $IntanExp_{it}$		0.0587		0.0601
		(0.00338)		(0.00331)
Observations	147,827	205,799	147,827	205,799
R-squared	0.948	0.942	0.896	0.890
Fixed Effects:	Firm; Year			

Notes: OLS estimations. Dependent variables: columns (1)-(2), *ln* μ_{it} *(Baseline)* indicates firm-level markups following the methodology in Appendix C; columns (3)-(4), *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). *ln* $Intan_{it}$ indicates the log of firm-level intangible assets, as measured in firm-level balance-sheets. By taking logs, we exclude those firms with zero levels of intangible fixed capital. The variable *ln* $IntanExp_{it}$ indicates the log of Intangible Operating Expenses, measured as revenues minus production costs, operating profits and depreciation. All regressions include controls for a firm's Current Liabilities and Cash holdings. Standard errors are in parentheses and clustered at the firm level.

Table A.3: Intangible Intensity Across Indutries

Industry (NACE Rev. 4)		Intangible Intensity (Overall)	R&D Intensity
10	Food Products	0.27	0.00
11	Beverages	0.30	0.00
13	Textiles	0.40	0.05
14	Wearing Apparel	0.29	0.00
15	Leather Products	0.27	0.01
16	Wood Products	0.11	0.03
17	Pulp, Paper, & Products	0.11	0.01
18	Printing and Publishing	0.23	0.02
19	Coke and Refined Petroleum	0.13	0.01
20	Chemicals, and Products	0.27	0.03
21	Pharma Products	0.58	0.76
22	Rubber & Plastic Products	0.20	0.03
23	Non-metallic mineral Products	0.20	0.01
24	Basic Metals	0.12	0.01
25	Fabricated Metal Products	0.20	0.01
26	Computer & Electronics	0.36	0.07
27	Electrical Equipment	0.23	0.05
28	Machinery & Equipment n.e.c.	0.21	0.02
29	Motor Vehicles, (Semi-)Trailers	0.16	0.00
30	Other Transport Equipment	0.17	0.03
31	Furniture	0.23	0.01
32	Other Manufacturing	0.41	0.06
33	Repair and installation of machinery and equipment	0.12	0.01

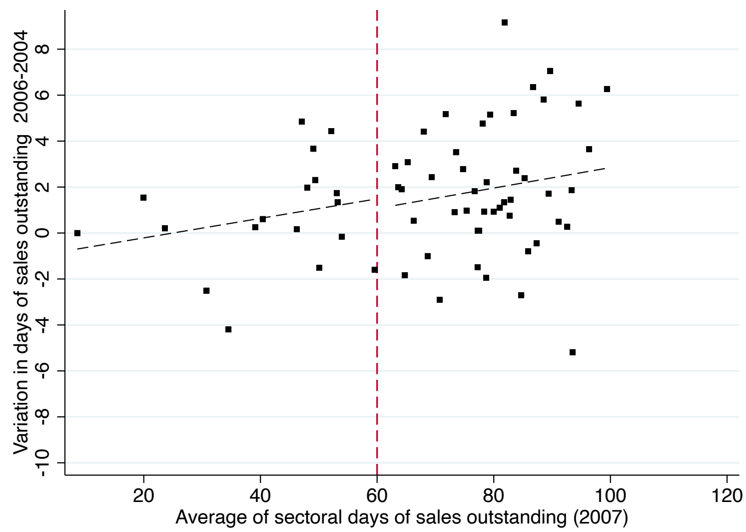
Notes: The table reports intangible intensity calculated from Compustat data for all U.S. firms from 2004 to 2007. The Overall Intangible intensity is measured as firm-level Sales and General Administrative Expenses (SG&A) over total sales. The R&D intensity is measured as firm-level R&D expenses over total sales. Firm-level estimates are aggregated at the 4-digit NACE sector level by taking the median-firm intangible intensity ratio of each sector. Standard concordance tables from eurostat.com are used to convert 6-digits NAICS industries in Compustat to 4-digit NACE industries in ORBIS. Source: authors' calculations on Compustat data.

Table A.4: External Financing Dependence Across Industries

Industry Code	Industry (NACE Rev. 4)	EFD (Capital Expenditures)	(Total Assets Expenditures)
10	Food Products	-1.00	0.87
11	Beverages	0.31	0.94
13	Textiles	0.06	0.91
14	Wearing Apparel	-0.25	0.93
15	Leather Products	-0.09	0.92
16	Wood Products	-0.10	0.91
17	Pulp, Paper, & Products	0.18	0.91
18	Printing and Publishing	0.01	0.90
19	Coke and Refined Petroleum	0.22	0.92
20	Chemicals, and Products	0.31	0.91
21	Pharma Products	0.34	0.91
22	Rubber & Plastic Products	0.07	0.91
23	Non-metallic mineral Products	-0.48	0.89
24	Basic Metals	0.24	0.92
25	Fabricated Metal Products	-0.15	0.89
26	Computer & Electronics	0.30	0.91
27	Electrical Equipment	0.09	0.90
28	Machinery & Equipment n.e.c.	0.26	0.92
29	Motor Vehicles, (Semi-)Trailers	0.00	0.92
30	Other Transport Equipment	-0.15	0.93
31	Furniture	0.00	0.91
32	Other Manufacturing	-0.66	0.85
33	Repair/Inst. of Machinery & Equipm.	-0.29	0.90

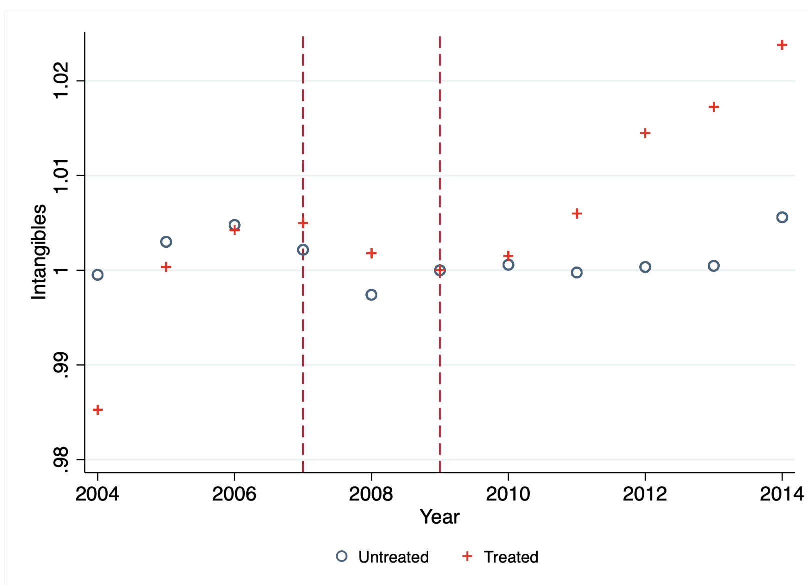
Notes: The table reports measures of External Financing Dependance (EFD) at the industry level calculated from the baseline ORBIS dataset on all French firms from 2004 to 2007. As in Rajan and Zingales (1998), EFD is defined as (Capital Expenditures (CE) - Cash Flows (CF))/CE. Column (1) reports EFD measures based on total capital expenditures as reported in ORBIS; column (2) reports a measure based on expenditures on total assets. Firm-level estimates are aggregated at the 4-digit NACE sector level by taking the median firm ratio of each sector.

Figure A.1: Impact of the policy on payment days, Placebo (2004-2006)



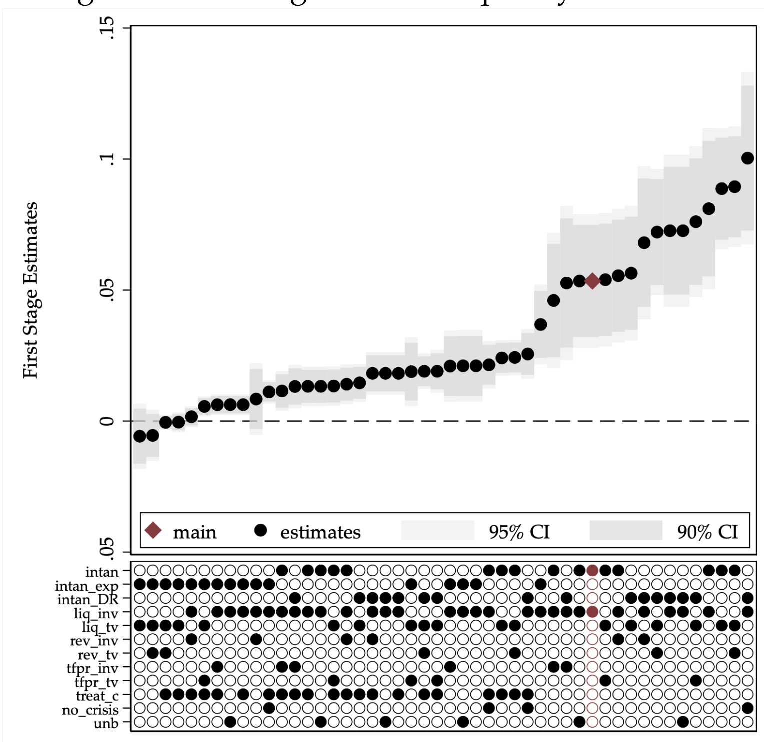
Notes: This graph displays the difference in days of sales outstanding between 2004 and 2006 as a function of the average DSO in 2004 for each NACE-4 digit industry. Since the years 2004 and 2006 were unaffected by the policy shock, we consider this figure as a placebo test of our measure of exposure to the policy shock. 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 A.2: Trends in Intangible Capital – Treatment vs. Control



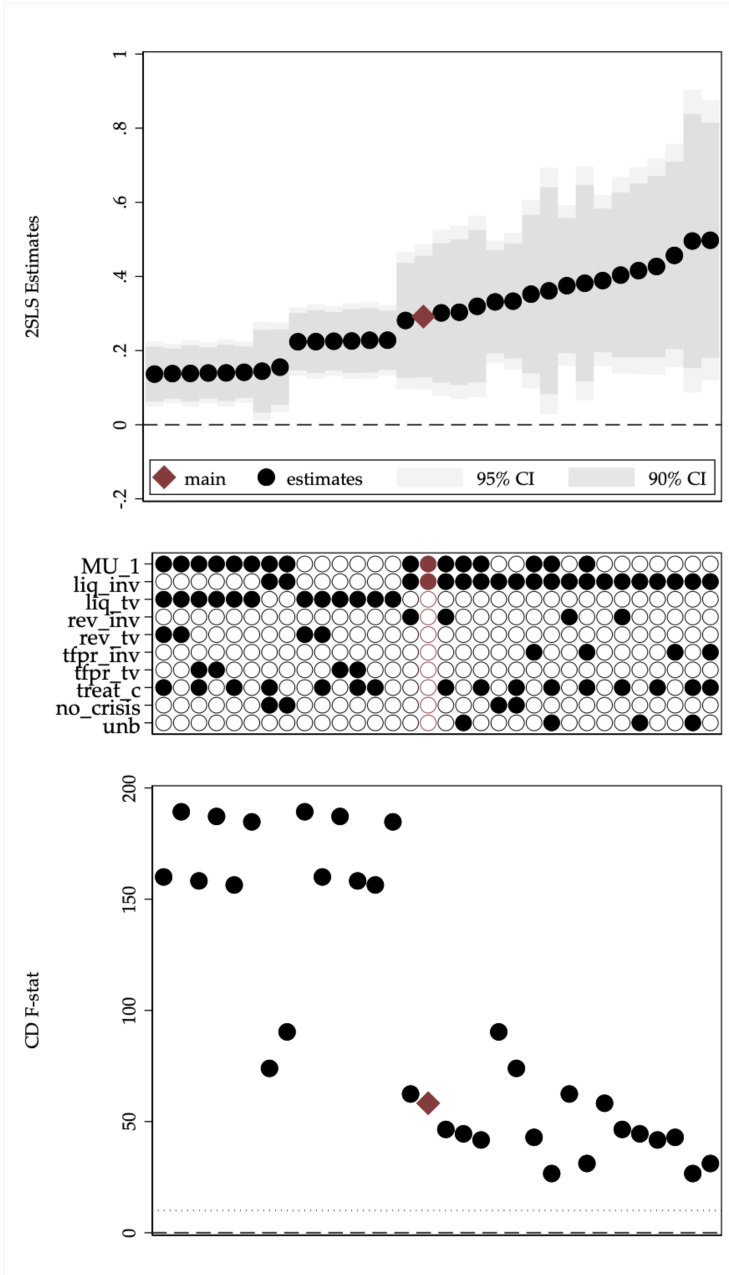
Notes: The graph shows trends (mean by year) in intangible capital (intangible assets) for both treatment and control group using the treatment definition T_1. The raw variables are normalized by the mean of treated and untreated firms in 2009.

Figure A.3: Intangibles and Liquidity – Robustness



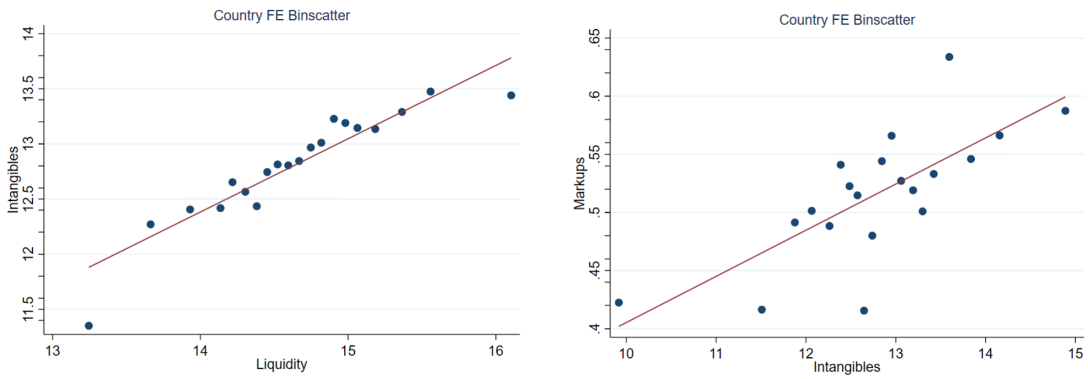
Notes: The figure reports the estimates of β from 48 variations of regression equation equation (5). Each circle inside the main graph corresponds to the point estimate, and we show both 90% and 95% confidence intervals. The bottom of the graph indicates the features of each of the 48 specifications. A dark circle means that the specification includes that feature. The red diamond corresponds to our baseline one, from column 1 of Table 2. The features are as follows: 'intan' refers to the baseline intangible measure; 'intan_exp' measures intangibles as operating expenses unrelated to variable production costs, while 'intan_DR' measures intangibles as fixed cost expenditures, based on De Ridder (2020). The terms 'liq_inv', 'liq_tv', 'rev_inv','rev_tv','tfpr_inv', and 'tfpr_tv' all refer to different sets of controls added to the estimation. 'liq' 'rev' and 'tfpr' stand for liquidity controls, sale control, and tfpr control, respectively, while the suffix 'inv' and 'tv' refer to whether these controls are time invariant (interacted with post dummy) or time-varying, respectively. The term 'treat_c' refers to whether or not the treatment variable is continuous; this term is black whenever we use $T2$ as our main treatment definition. 'no_crisis' refers to specifications where we leave out the years 2009 and 2010. Finally, 'unb' refers to specification ran on the original, unbalanced sample. All specifications include firm and year fixed effects. The figure was constructed with the STATA package speccurve.

Figure A.4: Markups and Intangibles – Robustness

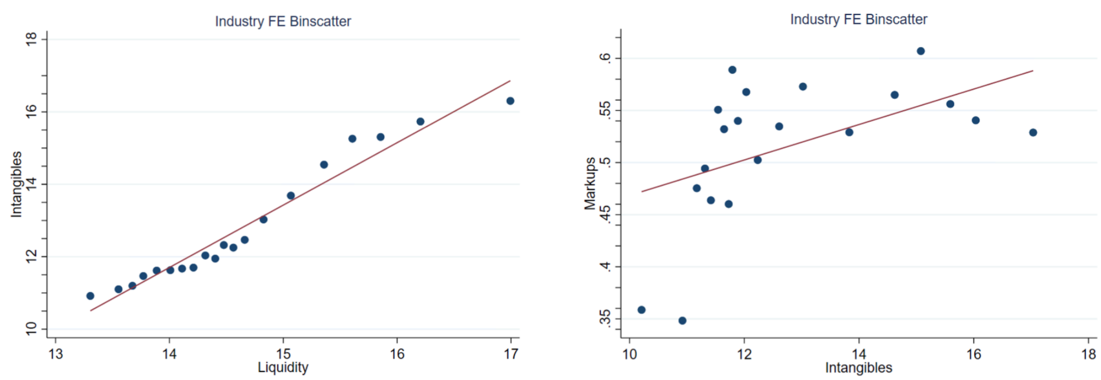


Notes: The figure reports the estimates of β from 32 variations of regression equation equation (7). Each circle inside the main graph corresponds to the point estimate, and we show both 90% and 95% confidence intervals. The bottom of the graph indicates the features of each of the 32 specifications. A dark circle means that the specification includes that feature. The red diamond corresponds to our baseline one, from column 1 of Table 4. The features are as follows: 'MU_1' refers to the baseline markup measure; this option is not selected when we use the alternative markup measure based on "non-parametric" output elasticities. The terms 'liq_inv', 'liq_tv', 'rev_inv','rev_tv','tfpr_inv', and 'tfpr_tv' all refer to different sets of controls added to the estimation. 'liq' 'rev' and 'tfpr' stand for liquidity controls, sale control, and tfpr control, respectively, while the suffix 'inv' and 'tv' refer to whether these controls are time invariant (interacted with post dummy) or time-varying, respectively. The term 'treat_c' refers to whether or not the treatment variable is continuous; this term is black whenever we use $T2$ as our main treatment definition. 'no_crisis' refers to specifications where we leave out the years 2009 and 2010. Finally, 'unb' refers to specification ran on the original, unbalanced sample. All specifications include firm and year fixed effects. The figure was constructed with the STATA package speccurve. The bottom panel of the figure reports ue to the limited flexibility of the package, we do not report the CD F-Stat for all specifications, which is always well exceeding the Stock and Yogo (2005) rule-of-thumb cutoff of 10.

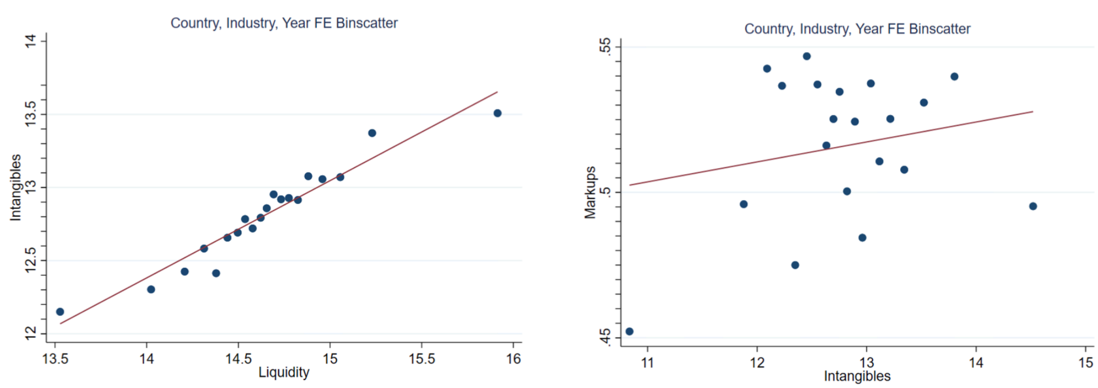
Figure A.5: Aggregation - Fixed Effects Regressions



a) *Country Fixed Effects*



b) *Industry Fixed Effects*



c) *Country, Industry, Year Fixed Effects*

Notes: The Figure shows binscatter plots of the correlations between intangibles and liquidity (left column) and markups and intangibles (right column) after purging for fixed effects at the country (first row), industry (second row), and country, industry, and year level (third row). Each observation is an industry×country×year cell. Liquidity is measured as current liabilities; markups are measured as turnover over cost of good sold. Aggregation is done using sample weights for each firm.

B A Formal Model of Intangibles, Markups, and Financial Frictions

This section introduces a theoretical model to illustrate the equilibrium relationship between liquidity constraints, intangible capital, and markups. We build the most parsimonious model that allows us to address this question in the context of our data. The model serves two purposes. First, it highlights the key theoretical mechanisms and motivates the empirical analysis, by emphasizing the role of confounding factors. Second, it motivates our approach to production function and markups estimation. We describe this approach in details in Appendix C.

B.1 Demand

A representative worker derives utility from consumption of differentiated varieties of the final good and supplies labor to firms. Each variety of the final good is produced by a different firm. The focus on markup heterogeneity requires departing from the assumption of CES utility and monopolistic competition. We maintain the assumption of monopolistic competition and consider a general demand system for the differentiated goods that encompasses a number of prominent alternatives to CES, following Arkolakis et al. (2018). The consumer's demand for variety $x \in \mathcal{X}$ when income is $Y = wL$ and prices are $\mathbf{p} = \{p(1), p(2), ..p(x), ..\}$, is

$$q(x) = \gamma D\left(\frac{p(x)}{P}\right) Q, \tag{8}$$

where $D(y) \in \mathcal{C}^2(y)$ is a twice continuously differentiable function, with $y \equiv p/P$ and $D'_y < 0$. 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.[21]

We denote the elasticity of demand as $\varepsilon(y) = -\partial \ln D(y)/\partial \ln y > 1$. We impose that $\varepsilon' > 0$, that means that demand is more elastic for firms that charge a higher relative price. This assumption is consistent with the large empirical evidence on variable markups,

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

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

with $\beta \in \{0, 1\}$ and $H(\cdot)$ strictly increasing and concave. If $\beta = 1$, preferences are homothetic. Conversely, if $\beta = 0$, preferences are non-homothetic unless utility functions are CES.

showing that more efficient firms have lower prices and charge higher markups over marginal costs.[22]

B.2 Firms and Technology

Each firm is a monopolist for the variety it produces. There is free entry into production, subject to an initial entry cost $f_e \leq 0$ in units of the numeraire. Upon entry into the production stage, each firm draws a random efficiency level $\phi \in \mathbb{R}_+$, as in Melitz (2003).

Producers may choose to combine labor with a modern technology featuring a high upfront cost in exchange for a proportional reduction in the unit labor requirement (Hsieh and Rossi-Hansberg, 2019; De Ridder, 2020). This technology can be thought of as knowledge-based intangible capital (Peters and Taylor, 2017). Hereafter, in a slight abuse of terminology, we will refer to it simply as intangible capital. Each firm may decide the fraction $s \in [0, 1)$ of unit labor requirement reduction associated with its investment; the larger the desired s, the larger the upfront cost. We denote this cost by $f(s, \phi)$ and assume that $f(\cdot, \phi)$ is increasing and convex in the first argument, with $f'_\phi < 0$ and $f(0, \phi) = 0$. This formulation implies that for a given level of investment s, more efficient firms pay lower upfront costs.

For a firm with productivity ϕ, the cost $TC(q; \phi)$ of producing q units of the final good will be given by the sum of variable production costs and the upfront cost $f(s, \phi)$:

$$TC(q; \phi) = (1 - s(\phi))\phi^{-1}q + f(s(\phi), \phi), \tag{9}$$

where $s(\phi)$ is the optimal investment of firm with productivity ϕ, and where we normalized the unit wage to one $w = 1$. Given the assumption on demand and market structure, the optimal price is a (variable) markup over the marginal cost

$$y(\phi) = \mu\left(y(\phi)\right)(1 - s(\phi))\phi^{-1}P^{-1}, \tag{10}$$

where $y(\phi) \equiv \frac{p(\phi)}{P}$ and $\mu(y) \equiv \varepsilon(y)/(\varepsilon(y) - 1)$. Log-differentiating both sides of equation (10), it's easy to show that $\Delta^y \equiv \frac{d \ln y}{d \ln s} = -\frac{1}{1+\Gamma_y}\frac{s}{1-s} < 0$, where $\Gamma_y \equiv -\frac{d \ln \mu}{d \ln y} > 0$ is the elasticity of the markup with respect to the relative price, which is positive due to the restrictions on the demand function. Similarly, $\Delta^\mu \equiv \frac{d \ln \mu}{d \ln s} = -\Gamma_y \frac{d \ln y}{d \ln s} > 0$. Thus, the price y is a decreasing function of the intangible capital s, while markups increase in s.

TESTABLE PREDICTION 1. *All else constant, firms that invest more in intangibles charge higher*

[22] See, e.g., Burstein and Gopinath (2014); Arkolakis and Morlacco (2017) for reviews of the empirical literature.

markups over marginal costs.

Plugging equation (10) into the firm's profit maximization problem

$$\max_s \left(\mu\left(y\right)-1\right)\left(1-s\right)\phi^{-1}D\left(y\right)Q-f(s,\phi),$$

one can solve for the optimal choice of intangibles $s = s(\phi)$ from the associated FOC:

$$\phi^{-1}Q = \frac{f'(s,\phi)}{D(s,\phi)} \implies s(\phi) = h(\phi;Q). \tag{11}$$

Under some conditions on $f(\cdot)$ and $D(\cdot)$ that we maintain throughout, it is possible to show that the equilibrium level of intangible capital as an increasing function of ϕ, that is, $s'_\phi > 0$.

B.3 Credit-constrained Producers

One crucial assumption of the above model is that firms must pay the technology costs up-front. These costs are substantial. In 2000-2013, the overall share of intangible investment in intangible investment in GDP was above 7% within the EU14 economies, with the share of R&D expenditures over GDP fluctuating around 2.1%. In France, the intangible share in GDP (8.7%) outpaced tangible investment over the same period (7.1%) (Corrado et al., 2018).

The model so far has implicitly assumed that there exist perfect financial markets so that any firm that could profitably use intangibles will find some investors to finance the initial investment. However, in the real world, such financing options may not be easily accessible to firms. A critical feature of intangible capital is that it cannot be easily verified or liquidated and, as such, cannot be pledged as collateral to raise external financing. Most firms will thus need to use current liquidity to finance investment (Bates et al., 2009; Lim et al., 2020; Falato et al., 2020).

Hereafter, we will take an extreme view on the limitations of financial markets that firms may face by imposing that a firm must rely on its existing liquidity to cover the fixed entry cost and the investment in intangibles. We assume that each firm is endowed with liquidity $A = A(\phi, \theta) \geq 0$, in units of the numeraire. The term $A(\phi, \theta)$ captures the fact that a firm's liquidity may depend on firm-level efficiency ϕ, through a firm's history of accumulating cash for instance, and pledgeable assets $\theta \in \mathbb{R}_+$, reflecting all other sources of liquidity not directly related to ϕ. Notably, the correlation between productivity and liquidity constraints is not perfect, as firms with the same ϕ may own assets of different pledgeable value θ.[23] These assumptions reflect two properties of intangibles. First, liquidity constraints are more severe for intangible investment than for other types of investment. Second, firms are more or less severely hampered by liquidity constraints, in ways not perfectly correlated with their current productivity (Chaney, 2016).

B.4 Intangibles and Financial Frictions

Given the above assumptions, a firm's liquidity constraint can be written as follows:

$$A(\phi,\theta) - f_e \geq f(s,\phi). \tag{12}$$

Given aggregate variables, the equilibrium of this model is simple to characterize. Let $s^*(\phi)$ denote the frictionless level of intangible capital from equation (11). For firms whose liquidity constraint is *not binding*, i.e., such that $(\phi,\theta) : A(\phi,\theta) - f_e > f(s^*(\phi),\phi)$, the intangible investment is at its frictionless rate, i.e. $s(\phi) = s^*(\phi)$. For firms whose liquidity constraint is *binding*, i.e., such that $(\phi,\theta) : 0 < A(\phi,\theta) - f_e < f(s^*(\phi),\phi)$, the intangible investment is lower than its frictionless level and it is such that $s(\phi) : f(s(\phi),\phi) = A(\phi,\theta) - f_e$. Finally, when firms do not have any cash holdings left after upon payment of the fixed entry cost, i.e., $(\phi,\theta) : A(\phi,\theta) - f_e = 0$, the intangible capital is such that $f(s(\phi),\phi) = 0$, such that $s(\phi) = 0$.

TESTABLE PREDICTION 2. *With perfect financial markets, or when liquidity constraints are not binding, differences in firm-level intangible investment across firms only depend on firm-level efficiency. For liquidity constrained firms, all else constant, intangible investment increases in firm-level liquidity A.*

B.5 From the Theory to the Data

We now discuss how we transition from the model to the empirical analysis. We use the model to motivate both the analysis in Section 3, that is interested in the effect of liquidity constraints on intangible investment, and the analysis in Section 4, which studies the relationship between intangibles and markups. These relationships are governed by testable predictions 2 and 1, respectively.

One may think that simple OLS regressions could inform the magnitude of such correlations. However, the model shows that positive correlation between liquidity and intangible capital may be spurious insofar as firms' cash holdings depend on firm-level

[23] We let (ϕ,θ) to be drawn from a joint distribution with c.d.f. $F(\phi,\theta)$ over $\mathbb{R}_+ \times \mathbb{R}_+$. We remain agnostic on the shape of the joint distribution F.

characteristics, such as efficiency or idiosyncratic firm-level demand shocks. Therefore, the empirical analysis must isolate changes in liquidity that originate from factors unrelated to idiosyncratic firm characteristics, which in the model are captured by the term θ. In Section 3, we deal with this endogeneity by exploiting quasi-experimental variation in liquidity induced by a policy reform improving the repayment terms of firms. We interpret the policy shock as a shock to θ.

Similar unobserved factors may confound estimates of the relationship between intangible capital and markups. More efficient firms invest more and charge higher markups, leading to endogeneity bias in OLS regressions. In Section 4, we deal with this endogeneity by instrumenting intangible capital with the policy shock, which allows us to isolate the effect of s on firm-level markups and profitability.

C Estimation of Firm-level Markups

In this section, we describe our procedure for estimating measures of markups at the firm-level. Section C.1 describes our production function estimation procedure. We depart from more standard approaches by including productivity-enhancing intangibles, in line with theories of markup-enhancing intangibles including the theoretical framework in Appendix B. Accounting for intangibles in the estimation of production functions has been shown to be important to avid biases in the estimation of output elasticities, and the estimation of both markups and productivity thereof (CompNet, 2020).

Section C.2 describes how we estimate firm-level markups from the production function estimates.

C.1 Production Function Estimation

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

$$Q_{it} = e^{\omega_{it}+\phi_{it}+\epsilon_{it}} F_t(K_{it}, \mathbf{V}_{it}; \beta), \tag{13}$$

where Q_{it} is physical output, obtained using tangible capital (K_{it}), and a set of variable inputs such as labor (L_{it}) and material inputs (M_{it}) captured by the vector $\mathbf{V}_{it}$.[24]

The term $e^{\omega_{it}+\phi_{it}+\epsilon_{it}}$ captures total factor productivity, which we model as a function of an idiosyncratic component ω_{it}, known by the firm but unknown by the econometrician, an endogenous component $\phi_{it} = \phi(S_{it}, \omega_{it})$ that captures the productivity advantage of firms that invest in intangibles, which we write as an increasing function of intangible expenditures S_{it} and idiosyncratic productivity ω_{it}, and a term ϵ_{it} capturing idiosyncratic shocks to production unobserved to the firm. Neither ω_{it} nor ϕ_{it} nor ϵ_{it} are observed by the researcher. As explained in Section 2, in our data a measure of total expenditures on intangibles S_{it} is directly observed.

We consider a flexible Translog (TL) specification of the function F_t for our main results. We thus write (13) in explicit form as:

$$\begin{aligned} q_{it} \quad = \quad & \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_{kk} k_{it}^2 + \beta_{ll} l_{it}^2 + \beta_{mm} m_{it}^2 + \\ & \beta_{kl} k_{it} l_{it} + \beta_{lm} l_{it} m_{it} + \beta_k m k_{it} m_{it} + h(\omega_{it}, s_{it}) + \epsilon_{it}, \end{aligned} \tag{14}$$

where $h(\omega_{it}, s_{it}) \equiv \omega_{it} + \phi(\omega_{it}, s_{it})$ is the productivity term written in compact form and where lower-case letters denote log variables.

[24]The function $F(\cdot)$ satisfies standard regularity conditions.

As it is well-known in the literature, the estimation of (14) requires dealing with several biases. Not only do 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 the estimation, potentially large when markups are heterogeneous across firms (De Loecker and Goldberg, 2014; Foster et al., 2008).

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

A1 *Firms take the price W_{it}^X of inputs $X = K, M, L$ 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 data on output quantities are not available and because in the model we explicitly allow for markup differences across firms. Recently, De Ridder et al. (2021) have shown that while the level of revenue-based markups is affected by bias, their dispersion across firms and correlation with other measures of firm-level profitability are not. We thus leverage their result and use revenue data in what follows. We write:

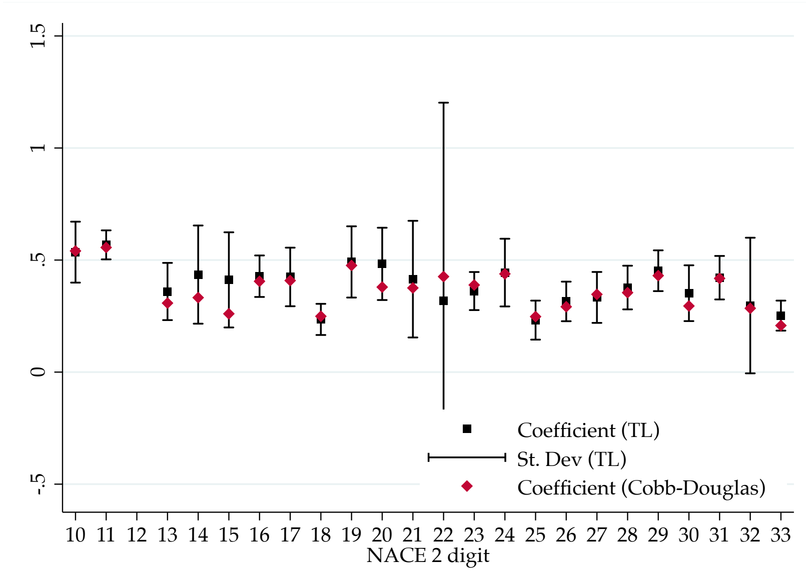
$$
\begin{aligned}
r_{it} \quad = \quad & \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_{kk} k_{it}^2 + \beta_{ll} l_{it}^2 + \beta_{mm} m_{it}^2 + \\
& \beta_{kl} k_{it} l_{it} + \beta_{lm} l_{it} m_{it} + \beta_k m k_{it} m_{it} + h(\omega_{it}, s_{it}) + \underbrace{p_{it} + \epsilon_{it}}_{u_{it}},
\end{aligned} \tag{15}
$$

where u_{it} is the new error term that includes the unobserved output prices. Following the literature, we estimate (15) using the Ackerberg et al. (2015) two-stage GMM procedure. The procedure involves a first-stage regression that purges firm output of measurement error and transitory productivity shocks, and a second-stage that identifies the production function by imposing structure on the productivity process to identify the true parameters. The identifying restrictions are that the TFP process's innovation is not correlated with current capital and with last period variable inputs. These moment conditions are fully standard in the production function estimation literature.

Figure C.1 plots the estimates of the output elasticities of the material input from equation (15) across 2-digit NACE industries, plus and minus one standard deviation. The Figure also includes the estimates of the same output elasticity obtained when specifying a Cobb-Douglas production function instead.

Productivity Note that our discussion implies that physical productivity $TFPQ_{it} \equiv (\omega_{it} + \phi_{it})$, cannot be recovered from our procedure. We can identify an estimate of the

Figure C.1: Output Elasticities



Notes: The graph shows estimates of the output elasticities of the variable input, across 2-digit NACE industries. The black lines and dots are the estimate obtained from a Translog (TL) specification of the function F_t, plus and minus one standard deviation. The red diamonds are the Cobb-Douglas point estimates.

term $\widehat{h_{it} + p_{it}}$ as a residual of equation (15). This term reflects both physical efficiency and the average price of firm i, and is thus a measure of total factor revenue productivity.

C.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 (1988) 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 (13) and choosing inputs so as to minimize variable costs. Unders Assumption A1, the first order condition associated with the choice of the material input can be written as:

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

where $\theta_{it}^m = dq_{it}/dm_{it}$ is the output elasticity of the material input and $\alpha_{it}^m \equiv \frac{E_{it}^m}{R_{it}}$ is the share of expenditures on material inputs E_{it}^v over total firm revenues R_{it}. Both input expenditures and revenues are directly observed in most firm-level data. Under the TL specification of equation (13), the output elasticity of the material input can be obtained as:

$$\hat{\theta_{it}^m} \equiv \frac{dq_{it}}{dm_{it}} = \hat{\beta}_m + 2\hat{\beta}_{mm}m_{it} + \hat{\beta}_{km}k_{it} + \hat{\beta}_{lm}l_{it}.$$

Markups are then computed as:

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