Liquidity as Competitive Advantage: The Role of Intangibles

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Abstract

This paper investigates how short-term financing, specifically trade credit, contributes to competitive advantage by facilitating the financing of intangible assets. The analysis draws on a rich dataset of French manufacturing firms from 2004 to 2014 and employs a difference-in-differences approach, using a policy reform on trade credit to generate quasi-experimental variation in corporate liquidity. Improved liquidity significantly boosts investment in intangibles, which in turn leads to increased markups and market shares. These results reveal a new channel through which liquidity may serve as a strategic competitive asset for companies, with implications for aggregate efficiency.

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1 Introduction

The global economy is undergoing a profound transformation. Traditional factors of production, such as physical capital and labor, are losing their role as primary drivers of economic growth. In contrast, intangible capital, such as intellectual property, brand equity, and patents, is taking center stage as a key determinant of a company's market value. Companies that invest in and effectively manage intangibles are better equipped to handle competition and capitalize on emerging market opportunities, thus improving their long-term resilience and profitability (Haskel and Westlake, 2018; Crouzet and Eberly, 2018).

Extensive literature indicates that investing in intangible capital is associated with higher productivity and profitability, both domestically and internationally.[1] Yet, the factors that drive intangible investments and the subsequent competitive advantage are less understood. This study suggests that access to short-term financing, such as trade credit, plays a role. We find that changes in trade credit terms significantly influence intangible investments, suggesting substantial liquidity constraints faced by firms. With improved liquidity, firms tend to increase their investment in intangible assets, which, in turn, leads to a strengthened competitive position, as measured by higher markups and market shares.

Section 2 motivates our analysis by delving into several theoretical mechanisms that link intangible investment to competitive advantage. These mechanisms include intangibles providing a cost advantage to firms (De Ridder, 2024), facilitating access to a broader customer base through competitive externalities (Morlacco and Zeke, 2021), or increasing returns to scale (Lashkari et al., 2024). An often implicit assumption in these theories is that financial markets are frictionless, which implies that the most efficient and largest firms are typically those who invest the most.

However, financial markets are far from perfect, particularly in the context of intangible assets (Hall and Lerner, 2010). Attributes such as high valuation uncertainty and low collateral value often hinder debt financing, forcing firms to rely on their liquidity as an alternative (Falato et al., 2023). This reliance on internal funding generates dispersion in the shadow cost of intangibles, leading to scenarios where liquidity-rich companies invest more, regardless of productivity differences. Thus, in the presence of liquidity constraints,

[1] See Crouzet and Eberly (2023) and Chintha et al. (2024) for respective discussions. A more comprehensive review of this literature is provided below.

access to short-term financing solutions like trade credit facilitates investment in intangibles, thereby leading to patterns of competitive advantage not necessarily linked to productivity.

We test these theoretical predictions in the context of a policy reform that led to quasi-experimental variations in liquidity among firms. Our empirical analysis specifically examines French manufacturing firms from 2004 to 2014 for two main reasons. First, we have access to comprehensive data from a representative sample of these firms. Second, this time frame includes the 2008-2009 financial crisis, a period marked by several French reforms aimed at improving corporate financing. We employ a difference-in-differences approach, leveraging changes in trade credit terms initiated by one such reform, to make causal inferences about our key relationships of interest. We particularly focus on the 2009 legislation that capped trade credit terms at 60 days for domestic transactions. This reform resulted in positive liquidity shocks for suppliers and negative ones for buyers whose previous payment periods exceeded this 60-day threshold (Beaumont and Lenoir, 2023).

We first test for liquidity constraints in financing intangibles. Our difference-in-differences approach leverages the cross-sectional variation in firms' exposure to trade credit prior to the reform. It examines whether firms that were further from the 60-day threshold (first difference) differentially changed their investment patterns following the policy change (second difference). Given that the reform affected firms differently depending on whether they were a net recipient or supplier of trade credit before 2009, we construct our treatment variable based on the *net* exposure to the shock. To mitigate the potential endogeneity of a firm's initial distance from the threshold to its future performance and investment returns, we include firm fixed effects and a rich set of control variables in all regression models.

We observe a significant positive effect of liquidity shocks on firm-level intangible assets. Our estimates imply that moving a firm from the 25^{th} to the 75^{th} percentile in the net distance from the threshold (i.e., a more positive liquidity shock) leads to a 4.4 percentage points (p.p.) increase in intangible assets and about 2 p.p. increase in intangible expenses. This evidence suggests the presence of liquidity constraints in the financing of intangibles, underscoring the impact of short-term financing options on asset accumulation. Consistent with our priors, the reform also seems to have strengthened the competitive position of the treated firms, for which we observe higher markups, market shares, and (domestic and export) sales post-reform compared to firms in the control group.

We then proceed to test the hypothesis that intangible investment is a major channel through which the trade credit reform has influenced competitive advantage. We begin by showing that intangible investment causally affects competitive advantage. To establish causality, we adopt an instrumental variable strategy that uses the firm-specific liquidity shock as an instrument for intangible investment. In line with the theoretical predictions, we find that firms with higher intangible investments charge significantly higher markups, which we use as our main proxy for competitive advantage.[2] Our findings are statistically and economically significant. The baseline estimates suggest that firms that increase their intangible expenditures by 10% can increase their price-cost margins by almost 8%. These estimates are robust to changing the set of controls in regressions and using alternative markup measures.

We then provide direct validation for the exclusion restriction, which asserts that the impact of the trade credit reform on firms' markups should operate uniquely through its influence on intangible assets. Nevertheless, the reform might have affected other dimensions of firms' strategic decisions beyond intangible investments. For example, investments in physical assets, such as machinery or automation technologies, could also contribute to a firm's competitive edge, and the reform might have facilitated such investments. Furthermore, the reform could have enhanced firms' borrowing capacity, enabling them to consolidate their market position and exert greater pricing power.

Supporting our exclusion restriction, we observe no significant differences in trends related to physical capital investment or borrowing capacity between the treatment and control groups post-reform. These results not only validate our instrumental variable strategy but also strengthen the argument that intangible assets are a crucial channel through which liquidity influences competitive dynamics. Furthermore, by highlighting the responsiveness of firm-level investment to the availability of short-term financing, our results resonate with the financial literature that emphasizes how the rise of intangibles has led to changes in the debt configurations of firms (Bates et al., 2009; Lim et al., 2020; Falato et al., 2023).

One challenge we face is the potential for measurement error in our data regarding the measurement of intangibles (Peters and Taylor, 2017). We validate our findings by showing that they remain consistent when using alternative measures of intangibles and when applying more stringent controls in our regression models. Additionally, we employ Com-

[2] In robustness exercises, we show that these results are robust to considering alternative metrics of competitive advantage, such as market shares and sales, both domestic and international.

pustat data to measure the degree of intangible intensity across industries, finding that the relationship between liquidity and intangibles is especially strong in industries with higher intangible intensity, reinforcing the credibility of our empirical interpretations.

Our empirical findings, consistent with theoretical predictions, yield two insights. First, they suggest that having access to short-term financing options, such as trade credit, can give producers a competitive advantage by enabling them to purchase intangible assets. Second, they suggest that financial factors may have contributed to recent trends in industry concentration and markups (De Loecker et al., 2020; Hall, 2018; Díez et al., 2021). Previous studies have associated the increase in markups with a rise in intangible capital, suggesting a correlation between higher markups and enhanced economic efficiency (Autor et al., 2020; Van Reenen, 2018; Crouzet and Eberly, 2018). Our research adds to this narrative by demonstrating that the distribution of intangible investments among firms is influenced by heterogeneous liquidity constraints, beyond mere firm-level productivity, potentially decreasing overall economic efficiency.

Literature Review This paper intersects with several strands of the existing literature. First and foremost, it contributes to the understanding of the role of liquidity and short-term financing in determining a firm's competitive advantage.

Previous studies have demonstrated that liquidity, beyond its role as a precautionary asset, significantly influences a firm's performance in the product market.[3] Fresard (2010) shows that firms with significant cash reserves are more likely to secure market share gains, especially in scenarios of heightened product market competition, such as after a reduction in import tariffs. Campello (2006) demonstrates a negative correlation between debt financing and product market performance. Focusing on the dynamics of business cycles, Chevalier and Scharfstein (1995), Campello (2003), and Gilchrist et al. (2017) present evidence that liquidity constraints affect firms' pricing strategies during economic downturns.

Evidence on the precise channels through which liquidity affects product market strategies is relatively limited. The existing literature emphasizes theoretical channels such as aggressive pricing (Bolton and Scharfstein, 1990; Chevalier and Scharfstein, 1995), or the threat of aggressive market behavior (Benoit, 1984). This study adds to this literature

[3] This discussion is part of a broader literature exploring the connections between product and financial market strategies, dating back to Brander and Lewis (1986), Kovenock and Phillips (1995), Phillips (1995), and Chevalier (1995), among others.

by presenting causal evidence of another channel through which short-term financing can enhance competitive advantage, which is by financing intangible assets.

Similarly, our study adds to the literature linking access to finance with a firm's ability to export (Amiti and Weinstein, 2011; Manova, 2008, 2013; Paravisini et al., 2015; Chaney, 2016). Specifically, our findings uncover a new dimension in which finance impacts a company's export competitiveness – and potentially its access to international markets – namely, through competitive advantage. The importance of competitive advantage has been widely recognized within the realm of international trade, both theoretically and empirically.[4] A novel insight from our research is that the roles of access to finance and competitive advantage in facilitating a company's entry into international trade are potentially interconnected through intangibles, in addition to productivity.

We also engage with the literature exploring the significance of trade credit for a firm's competitiveness. As a major source of short-term financing in domestic markets, trade credit is widely recognized as a strategic asset for firms (Petersen and Rajan, 1997; Wilner, 2000; Smith, 1987). Demir and Javorcik (2018) provides empirical evidence that the ability to offer trade credit serves as a competitive tool for exporters targeting highly competitive markets, acting as an alternative to low prices. Beaumont and Lenoir (2023) demonstrate how financial constraints can hinder a firm's efforts to reconnect with customers who withdrew during economic downturns, using the French reform on trade credit terms for empirical analysis – the same reform used in our study. Our paper complements their findings by showing that improvements in trade credit terms enhance a firm's competitive position, by facilitating investments in intangible assets broadly defined.

The rest of the paper is organized as follows. Section 2 establishes a theoretical link between liquidity, intangibles, and competitive advantage and lays the groundwork for the empirical analysis that follows. Section 3 presents our data and variable construction. Section 4 outlines the empirical strategy and reports the main empirical findings. Section 5 concludes and discusses directions for future research.

[4]See, for example, Bloom et al. (2016); Aghion et al. (2009); Mayer et al. (2014, 2021), among others.

2 Theoretical Framework

In this section, we aim to establish a theoretical link between liquidity constraints, intangible investment, and competitive advantage. First, in Section 2.1, we review various theories that connect intangible capital with competitive advantage, noting that these theories often assume the absence of financial market imperfections. Following this, Section 2.2 examines how liquidity constraints might influence these relationships. Throughout this discussion, we formulate testable predictions that we will be bring to the data in Section 4.

2.1 Intangibles and Competitive Advantage

Several mechanisms can lead firms with higher intangible assets to increase their market shares and secure a competitive advantage. Here, we introduce three recent theories that establish such an equilibrium relationship.

In De Ridder (2024), intangible capital is conceptualized as a productivity-enhancing technology. Firms face a trade-off regarding the adoption of intangible capital, balancing an initial investment against a proportional reduction in variable costs.[5] Firms engage in Bertrand competition in the product market by setting prices. Within this framework, firms that extensively adopt intangible capital can attain lower marginal costs and charge higher markups compared to their counterparts with lower rates of intangible adoption. In turn, firms with significant intangible assets can dominate their markets, reducing the incentive for innovation and entry by other firms.

In Morlacco and Zeke (2021), intangible assets such as brand equity and customer capital play a pivotal role in shaping competitive advantage. The study proposes a theoretical framework in which companies compete for customer loyalty through advertising, which can effectively entice customers away from their competitors and thereby reduce market share for the latter. This competitive externality is more pronounced for larger firms, who have more customers and are, therefore, more likely to invest heavily in advertising. This strategy allows them to consolidate and expand their market share over time, highlighting the strategic importance of advertising in accumulating intangible capital and its long-term impact on market structure.

[5] See also Hsieh and Rossi-Hansberg (2023) for a similar theory of intangibles in service sectors.

A third mechanism is based on intangibles increasing the returns to scale at the firm level. This channel is emphasized by Lashkari et al. (2024), who highlights the critical role of heterogeneous IT adoption in shaping competitive dynamics and macroeconomic outcomes. The core empirical finding is that larger firms exhibit a higher elasticity in their demand for IT resources compared to other inputs, indicating a non-homothetic pattern in IT adoption. Theoretically, they show that as IT prices fall, larger firms – that adopt IT more intensively – experience enhanced returns to scale due to their ability to spread the fixed costs of IT over a larger output. This mechanism leads to a competitive advantage for larger firms, as it lowers their average costs relative to smaller firms, potentially deterring entry and fostering industry concentration.

A common implication of these theories is that intangibles contribute to a firm's competitive advantage, in the form of increased market share and/or markups. The first testable prediction follows:

Testable Prediction 1. *All else equal, firms that invest more in intangibles gain a competitive advantage through larger market share or markup.*

2.2 The Role of Liquidity Constraints

Intangible capital is mainly embodied in technology that requires significant development and maintenance costs (Haskel and Westlake, 2018; Crouzet and Eberly, 2018). These costs can be quite high. From 2000 to 2013, intangible investment as a percentage of GDP exceeded 7% within the EU14 economies, with R&D expenditures around 2.1% of GDP. Specifically in France, intangible investment's share of GDP (8.7%) surpassed that of tangible investment (7.1%) during the same period (Corrado et al., 2018).

The prevailing theories on intangibles often presume frictionless financial markets, implying that firms can easily obtain funding for investments. However, financing intangible assets presents challenges. Their low redeployability and verifiability complicate their use as collateral for external financing. Consequently, firms frequently rely on liquidity to fund intangible investments.

To highlight the implications of financial market imperfections, we adopt an extreme view by requiring firms to invest in intangible assets entirely through existing liquidity. Let ϕ represent the exogenous component of firm-level productivity, and let $f(\phi)$ denote the corresponding investment in intangible assets. Additionally, let $\theta \in \mathbb{R}+$ represent pledgeable assets that are contingent on ϕ.

Firms have initial liquidity $A = A(\phi, \theta) \geq 0$, such that $A'\phi > 0$ and $A'_\theta > 0$. Here, $A(\phi, \theta)$ suggests that a firm's liquidity is influenced by its idiosyncratic productivity ϕ, for instance through a history of accumulating cash, but also on pledgeable assets θ, encompassing all other liquidity sources not directly related to ϕ. A firm's liquidity constraint on intangible investment can thus be summarized by the following expression:

$$f(\phi) \leq A(\phi, \theta). \tag{1}$$

Let $f^*(\phi)$ denote the optimal level of investment in the absence of liquidity constraints. For firms with non-binding liquidity constraints, investment in intangibles remains at the optimal level, i.e., $f(\phi) = f^*(\phi)$. For those with binding constraints, namely, $f^*(\phi) > A(\phi, \theta)$, investment is below the optimal level, limited by available liquidity ($f(\phi) = A(\phi, \theta) < f^*(\phi)$).

The implications for testing liquidity constraints in intangible investment are clear:

$$\frac{\partial f}{\partial \theta} \begin{cases} = 0 & \text{if the liquidity constraint is not binding,} \\ > 0 & \text{if the liquidity constraint is binding.} \end{cases} \tag{2}$$

This leads to our second testable prediction:

Testable Prediction 2. *All else equal, an exogenous increase in a firm's liquidity should boost intangible investment if the firm faces liquidity constraints. It should have no e ect if there are no liquidity constraints.*

2.3 From the Theory to the Data

Before we proceed with the empirical analysis, it's important to address the challenges related to aligning our testable predictions with the available data. First, we face a measurement challenge. Theories linking competitive advantage to intangible assets consider a broad spectrum of assets, from IT to advertising expenditures. However, our dataset cannot measure intangibles precisely, but only (i) either as intangible capital as broadly defined, and only when incorporated from M&A, or (ii) as total operating expenses. This has two implications. First, our empirical analysis can only generally validate this class of models, while examination of the specific mechanisms is not feasible. Second, the imprecise measurement of intangibles might lead to measurement errors. To address these issues, we will examine heterogeneous effects across different industries and employ more refined industry-specific proxies where feasible.

Measuring competitive advantage, which is closely associated with a firm's market share, is even more challenging due to our dataset's lack of comprehensive sales data across all firms within an industry. We address this challenge by considering markups as our main proxy for competitive advantage.[6] This approach is supported by several theories that propose a direct correlation between markups and market shares (Atkeson and Burstein, 2008; Mrázová and Neary, 2017). Additionally, a significant body of empirical evidence suggests a positive correlation between markups and firm size, reinforcing the rationale for using price-cost margins as proxies for competitive advantage.[7]

The last challenge is endogeneity. Simple OLS regressions may pick up spurious correlations between liquidity and intangibles due to firm-specific characteristics like productivity or idiosyncratic demand shocks. Similarly, omitted variables could bias the relationship between intangibles and markups. For instance, firms with higher productivity tend to invest more and charge higher markups, leading to potential endogeneity in OLS estimates. In Section 4, we address these endogeneity issues by exploiting quasi-experimental variations in liquidity prompted by a policy change that improved firms' repayment terms in domestic transactions. Our empirical approach aims to distinguish liquidity variations, denoted by θ, from unique firm characteristics, symbolized by ϕ. We will interpret the policy shock as an exogenous shift in θ.

3 The Data

The empirical analysis is based on a panel dataset of French manufacturing firms from 2004 to 2014, sourced from the ORBIS database by Bureau van Dijk. The ORBIS database encom-

[6]We also present results using market shares as an alternative measure, and we find that they are consistent with our main findings. Nonetheless, we consider markups as the most reliable measure as it is less susceptible to selection issues.

[7]See Burstein and Gopinath (2014) and Arkolakis and Morlacco (2017) for reviews of the empirical literature.

passes an extensive array of balance sheet variables, covering profit accounts and financial variables. It provides information, both direct and indirect, about a firm's expenditure on intangible assets, markups, and liquidity.[8]

We classify a firm as a manufacturing firm if it reports manufacturing as its primary activity, and we 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 drop those firms that report the number of employees for less than 50% of the years in the sample, ending up with about 38,000 unique firms observed over time. Finally, we restrict our baseline sample to firms that enter before 2005 and exit after 2010.[9] We do so to guarantee that any given firm appears both before and after the policy shock in 2008/09, mitigating concerns about changing sample composition. Our final dataset is representative of the official size distribution of French firms within each two-digit industry.[10]

3.1 Variable Construction

Intangible Capital Generally, intangible capital refers to a firm's expenditures to develop knowledge, patents, software, or advertising to build customer capital, human capital, and distribution systems (Peters and Taylor, 2017).

In ORBIS data, a measure of intangible assets is directly reported as part of a firm's balance sheet.[11] This stock variable reflects the book value of intangible assets acquired by the firm during business combinations. We take this variable as our baseline measure of intangibles. Two potential issues with this measure of intangibles are that (i) it does not reflect any past intangible investment by the acquirer, thus underestimating the value of intangibles for those firms whose intangibles are primarily generated internally; (ii) selection bias on the sample of acquired firms could distort the observed allocation of intangibles from

[8] 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.

[9] Adjusting the initial and final years at the margin does not affect the results significantly. In robustness exercises, we show that all our results replicate if we used the original, unbalanced sample.

[10] 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.

[11] 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."

the typical stock in an industry.

For this reason, we also consider a second measure of intangibles, which refers to the company's current expenses not related to production costs. This flow measure is determined by the following accounting formula:

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

where "other operating expenses" include rent, inventory, and insurance. Since the variables on the right-hand side are observed, and assuming "other operating expenses" are proportional to intangibles, "operating expenses" may serve as a proxy for intangible expenses.[12]

One caveat to consider regarding this second measure is that assuming proportionality between intangible and operating expenses does not account for variations in how firms allocate their operating expenses over time, which could result in mismeasurement. While this concern is relevant, it becomes particularly problematic for our purposes if the "other" operating costs are specifically constrained by liquidity and significantly affect a firm's ability to set markups. However, we consider this possibility unlikely.

Other commonly used measures of intangible investment include R&D expenses or a fraction of SG&A (Peters and Taylor, 2017; Eisfeldt and Papanikolaou, 2013). Unfortunately, our dataset does not include a sufficiently large sample of firms with these more direct measures. Nonetheless, to strengthen our findings and validate the intangible measures used, we examine heterogeneous effects across industries. This analysis is conducted in Section 4.2, where we utilize Compustat data to classify industries based on their intangible intensity, adhering to these standard definitions of intangibles. Our results indicate that the main effects are particularly pronounced in industries with higher intangible intensity, suggesting that the proxies employed credibly capture intangible dynamics.

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,

[12] This proxy for intangible investment is positively correlated with the stock measure of intangibles, although weakly. 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.

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 is that 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 B. Consistent with theories of markup-enhancing intangibles, which we review in Section 4.3, 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 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 approach to estimating markups proposed by De Loecker and Warzynski (2012) has been widely used, it has recently faced skepticism regarding its validity. The primary critiques focus on the bias introduced by using revenue rather than quantity data to estimate the production function (Bond, Hashemi, Kaplan, and Zoch, 2021), and misspecification in the first stage (Doraszelski and Jaumandreu, 2021). However, De Ridder, Grassi, Morzenti et al. (2021) argue that although the *level* of revenue-based markups is affected by this bias, their *dispersion* across firms and correlation with other measures of firm-level profitability, which are critical for our analysis, remain unaffected. Moreover, they demonstrate that the specification of the first stage only minimally impacts the estimates of production function parameters. These findings lend support to our approach to markup measurement and the subsequent analysis.

Competitive Advantage: Other Variables Although we primarily use markups as our measure of competitive advantage, we also evaluate alternative metrics. The first alternative is a firm's market share, defined by its proportion of total industry sales, with industries categorized by NACE4 codes. Despite market shares being theoretically ideal indicators of competitive advantage, we do not use them as our baseline measure due to precision concerns in our dataset. Our dataset lacks information on all firms, leading to inaccuracies in calculating the denominator and potential selection biases. Additionally, we examine total firm sales and exports, which are directly reported in balance sheet data.

Table 1: Summary Statistics

	Observations:	Mean	St. Dev.	P25	Median	P75
Intangibles						
Intagible Assets	217,840	112,114	351,677	0	13,722	78,199
Intangible Expenses	215,658	1,625,099	4,049,165	95,722	322,330	1,230,620
Competitive Advantage						
Markup (Baseline)	217,858	1.337	0.789	0.800	1.100	1.667
Markup (Cost Shares)	217,857	1.666	0.868	1.156	1.427	1.873
Market Share	220,057	0.01	0.05	0	0.001	0.004
Sales	220,057	13,600,298	239,819,488	466,594	1,400,487	5,132,029
Exports	219,130	3,779,569	67,527,393	0	0	226,293
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 expressed in 2010 euros, using industry-wide deflators from the STAN Industrial Database. Statistics are averaged over all years in the sample.

3.2 Summary Statistics and Preliminary Evidence

Table 1 presents summary statistics for the key variables of interest in our baseline sample. As is expected for firm-level data, the dispersion of all these variables is substantial. Firms in the third quartile, on average, spend 14 times more on intangibles than firms in the first quartile and charge a more than twice higher markup over marginal costs. Dispersion in sales is even more substantial.

The table shows significant variability in the liquidity of firms, as evidenced by their current liabilities, cash reserves, and trade credit. Trade credit is measured using ‘Accounts Payable’ – the total debt a company owes to its suppliers at the end of the fiscal year – and ‘Accounts Receivable’ – the total amount of sales that buyers still owe to the company at the end of the fiscal year. The amount of trade credit averages around 15% of turnover for the median firm, highlighting the importance of trade credit as a crucial source of short-term finance for firms (Petersen and Rajan, 1997).

Tables A.1 and A.2 in the Appendix present preliminary evidence indicating positive correlations among liquidity, intangibles, and markups. Table A.1 displays simple OLS correlations between firm-level intangible capital and measures of liquidity. All regressions account for firm and year fixed effects. The findings reveal that, on average, firms with more intangible assets also have higher levels of liquid assets, which aligns with expectations based on the financial literature mentioned earlier. This suggests the importance of controlling for pre-existing di□erences in firm liquidity when conducting regressions to ensure comparisons between companies under similar initial conditions.

Table A.2 shows the results of OLS regressions of firm-level markups on intangibles. All columns include controls for firm-level liquidity, 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 e□ects. Results show that firms that spend more on intangibles also charge higher markups over marginal costs.

4 Empirical Strategy and Results

The goal of our empirical analysis is to explore the role of liquidity as a source of competitive advantage. Based on the predictions of our model, we investigate two key hypotheses: (i) under liquidity constraints, improved liquidity leads to increased investment in intangible assets by firms (testable prediction 2); and (ii) firms that invest more heavily in intangibles achieve a competitive edge, which is likely reflected in higher markups over marginal costs (testable prediction 1). We dedicate Sections 4.1 and 4.2 to the first hypothesis, detailing our use of a di□erence-in-di□erences approach for establishing causality. Section 4.3 focuses on analyzing the relationship between intangible investments and markups, and it also considers alternative explanations for the observed link between liquidity and competitive advantage.

4.1 The Effect of Liquidity Shocks on Intangible Investment

A substantial body of research in finance and macroeconomics examines the relationship between firm-level investment and cash measures to investigate liquidity constraints.[13] An important insight from these studies is that the correlation between intangibles and cash flow, such as the one in Table A.1, does not alone warrant causal interpretation. A firm's current cash holdings are often indicative of future investment prospects, leading to a potentially spurious link between investment and liquidity. The theoretical discussion in Section 2 simplifies the understanding of this endogeneity. Since liquidity is influenced by both exogenous

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

financial conditions and firm-specific productivity, discerning liquidity constraints requires distinguishing changes in liquidity that arise from factors not related to productivity, which are represented by the variable θ in our model.

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.[14] Our data and setting are well-suited for a similar exercise. We exploit quasi-exogenous variation in liquidity shocks across heterogeneous firms induced by a policy reform in France that affected trade credit terms. We interpret the policy shock as a shock to θ in the model.

Institutional Context 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. It prohibited French firms from accepting trade credit 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 (Beaumont and Lenoir, 2023).

We follow the literature 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 receivable over sales, multiplied by 365:[15]

$$\mathrm{DSO}_{it} = \frac{\text{Accounts receivable}_{it}}{\text{Sales}_{it}} \times 365. \tag{3}$$

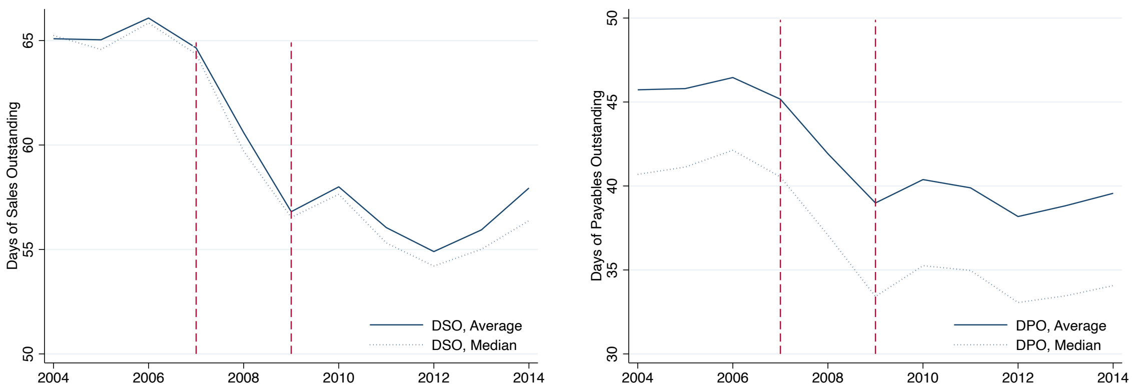
Similarly, we proxy the average time to *deliver* payments by firm i in year t as the number of days of payable outstanding (DPO, henceforth), which we construct as the ratio of accounts payable over sales, multiplied by 365:

$$\mathrm{DPO}_{it} = \frac{\text{Accounts payable}_{it}}{\text{Sales}_{it}} \times 365. \tag{4}$$

[14] Because experiments of this kind are hard to come by, researchers have used alternative econometric techniques to sidestep the econometric challenge with varying degrees of success. One common approach involves analyzing the differences in cash-investment correlations among groups of firms hypothesized to have different internal finance needs. 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.

[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.

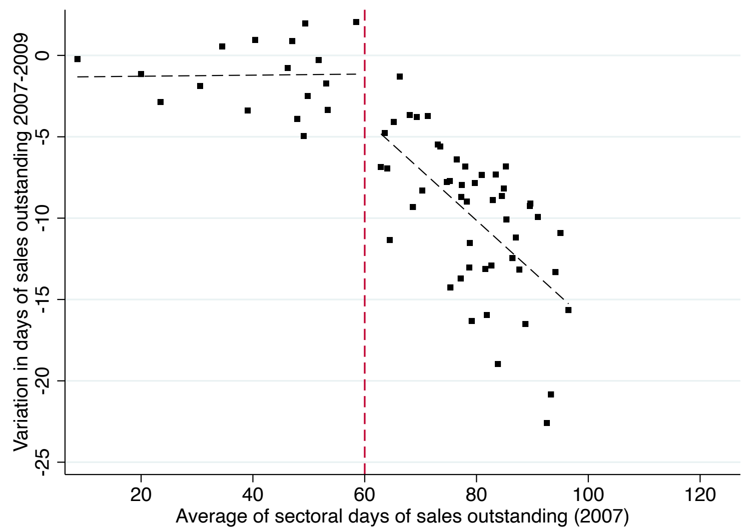
The average DSO before 2007 was 65.4 days for firms in our balanced sample, with a standard deviation of 43 days. The average DPO was substantially lower, at about 45 days, with a standard deviation of 30 days.

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. The figure shows a clear drop in payment terms for the average receiving firm, from around 65 days in 2007 to 57 in 2009 (left panel), pointing to 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.[16]

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 whose average 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

[16]Like Beaumont and Lenoir (2023), 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: 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 into 100 percentiles along the x-axis; the ordinate axis represents the average value of the y-variable in each percentile.

of considering changes in DSO between any two years before the policy shock, i.e., between 2004 and 2006. Before 2007, we do not see any 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.

Difference-in-Differences Strategy 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 group. In our setting, this means comparing changes in intangible asset holdings before and after the policy change for treated versus untreated firms. The critical (parallel trends) 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.

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:

$$T_{1,i} = \mathbb{I}\left\{\max\{DSO_{pre,i} - 60, 0\} - \max\{DPO_{pre,i} - 60, 0\} > 0\right\}, \tag{5}$$

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.[17] This definition treats around 50% of firms in the sample.

The second definition 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:

$$T_{2,i} = \max\left\{\max\{DSO_{pre,i} - 60, 0\} - \max\{DPO_{pre,i} - 60, 0\}, 0\right\} \tag{6}$$

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 groups 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:

$$\ln Y_{it} = \alpha + \beta \cdot Post_t \times T_{j,it} + Post_t \times X_i'\gamma + c_i + \delta_t + \epsilon_{it}, \quad j = 1, 2. \tag{7}$$

The dependent variable $Y_{it} = \{\text{Intan}_{it}; \text{IntanExp}_{it}\}$ 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,

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

Table 2: Liquidity Constraints and Intangibles

	(1)	(2)	(3)	(4)
Estimation:	DiD OLS			
Dep. Variable:	ln Intan$_{it}$		ln IntanExp$_{it}$	
T$_{1,it}$×Post$_t$	0.053***		0.021***	
	(0.013)		(0.007)	
ln (1+T$_{2,it}$)×Post$_t$		0.013***		0.006***
		(0.004)		(0.002)
Observations:	152,372	151,732	212,662	211,640
R-squared:	0.902	0.902	0.968	0.968
Fixed Effects:	Firm; Year			

Notes: The table shows DiD coefficients obtained by running OLS on equation (7). The dependent variable in columns (1)-(2) is the (the log of) firm-level intangible assets from the 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 (5), 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 (6), 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, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

starting with 2009, as the reform has been implemented since January of that year. The third term is an interaction between 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 robust standard errors clustered by firm. The estimates of the DiD coefficient of interest are positive and significant, indicating that the liquidity shock induced higher intangible investment in treated firms. Moving across the columns from left to right 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 columns (2) and (4), which consider the continuous treatment, indicate 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) p.p. following the policy change, and expenditure on intangibles by 2 p.p. (= 0.006 x 3.41), respectively.

Robustness Figure A.3 in the 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 by including controls for firm sales and productivity (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 (2024); (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.

4.2 Industry Heterogeneity

The findings in Table 2 may raise two concerns: first, measurement error may cause the variables $\textit{Intan}_{it}$ and $\textit{IntanExp}_{it}$ to capture operating costs other than expenses on intangibles; second, the quasi-experimental setting may pick up factors other than the liquidity shock to the businesses. This section examines two exercises designed to capture the heterogeneous treatment effect across industries in order to address both of these issues. Our findings alleviate the concerns by demonstrating that the relationship between liquidity and intangibles is particularly strong in industries that are both (1) more intangible-intensive and (2) more vulnerable to liquidity constraints.

We consider U.S. Compustat firm-level data – where detailed metrics of intangible spending and its components are available – to measure intangible intensity at the industry level (Demmou et al., 2020). The essential premise is that in a frictionless world, intangible intensity is akin to a sectoral technological characteristic that does not vary across countries. Since the U.S. can be considered a relatively frictionless market, its intangible asset levels are nearly optimal. We focus on the pre-reform years (2004-2007) and construct two measures of industry-level intangible intensity. The first measure is the ratio of Sales and General Administrative Expenses (SG&A) over sales. The second measure is the ratio of R&D over sales, which captures knowledge-based capital intensity.

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. This means that firms in high EFD industries are more likely to be dependent on external finance for their investment or liquidity constrained.

Appendix Table A.3 summarizes the two measures of intangible intensity by 2-digit sector; Appendix Table A.4 reports EFD by 2-digit sector instead. Both tables show substantial heterogeneity in these measures across industries.

We test for heterogeneous effects by modifying regression (7) to also include an interaction between industry intensity (ψ_s), treatment, and the post dummy:

$$\ln Y_{it} = \alpha + \beta_1 \cdot Post_t \times T_{j,it} + \beta_2 \cdot Post_t \times T_{j,it} \times \psi_{s,t0} + Post_t \times \tilde{X}_i' \gamma + c_i + \delta_t + \epsilon_{it}, \quad j = 1, 2, \quad (8)$$

where $\psi_{s,t0}$ is the industry intensity measure – either intangible or EFD intensity – before the policy reform, and where $\tilde{X}_{i(t)}$ includes both liquidity controls and the industry intensity measure.[18] The coefficient of interest is 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 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, knowledge-intensive (R&D-intensive) industries. Panel (b) shows instead that the liquidity shock's effect is stronger in industries that are more dependent on external finance, i.e., where liquidity constraints are expected to be more binding. All these results are in line with our prior that liquidity affects intangible investment.

4.3 Liquidity and Competitive Advantage: Evidence

We now explore the second hypothesis, which suggests that companies that invest more in intangible assets gain a competitive advantage, as reflected in increased markups.

As a first step, we examine how the reform influences a company's competitive position directly. The results are detailed in Table A.5 in the Appendix. The first two columns present

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

Table 3: Liquidity and Intangibles - Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)
Estimation:			DiD OLS			
Dep. Variable:		ln Intan_{it}			ln IntanExp_{it}	
Panel (a): Intangible Intensity						
$\text{T}_{1,it}\times\text{Post}_t$	0.053***	-0.000	0.030***	0.021***	0.007	0.008
	(0.013)	(0.017)	(0.014)	(0.007)	(0.009)	(0.007)
$\text{T}_{1,it}\times\text{Post}_t\times\text{SG\&A Int}_{s,t0}$		0.215***			0.056***	
		(0.045)			(0.019)	
$\text{T}_{1,it}\times\text{Post}_t\times\text{R\&D Int}_{s,t0}$			0.930***			0.544***
			(0.211)			(0.096)
Observations:	152,372	152,372	152,372	212,662	212,662	212,662
R-squared:	0.902	0.902	0.902	0.962	0.962	0.962
Panel (b): External Financing Dependence						
$\text{T}_{1,it}\times\text{Post}_t$	0.053***	0.084***	-0.024	0.021***	0.041***	0.016
	(0.013)	(0.018)	(0.034)	(0.007)	(0.010)	(0.020)
$\text{T}_{1,it}\times\text{Post}_t\times\text{EFD(Cap)}_{s,t0}$		0.025**			0.018**	
		(0.012)			(0.008)	
$\text{T}_{1,it}\times\text{Post}_t\times\text{EFD(Fixed Assets)}_{s,t0}$			0.152**			0.01
			(0.063)			(0.036)
Observations:	152,372	152,372	152,372	212,662	212,662	212,662
R-squared:	0.902	0.902	0.968	0.962	0.962	0.962
Fixed Effects:			Firm; Year			

Notes: The table shows the coefficients obtained by running OLS on equation (8). 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 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-digit NAICS industries in Compustat to 4-digit NACE industries in ORBIS. Source: authors' calculations on Compustat data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

the effects on (log) markups, our primary indicator of competitive advantage, while columns (3)-(8) consider other firm-level outcomes, such as market shares, (log) sales, and (log) export revenues.[19] The findings align with theoretical expectations, showing that liquidity shocks enhance firms' competitive positions across various measures. Notably, the size of the coefficients is relatively small, particularly when compared to the impact on intangible investments.

Next, we more closely examine whether liquidity affects competitive advantage, specif-

[19] Market shares are calculated as the ratio of firm i's sales to the total sales within its industry, with industries defined by NACE4-digit codes.

Table 4: Markups, Intangibles and Liquidity

	(1)	(2)	(3)	(4)
Estimation:		2SLS		
Dep. Variable:		ln μ_{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)
Observations:	152,372	151,732	212,662	211,640
Fixed Effects:		Firm; Year		
F-Stat:	58.25	41.73	37.93	39.76

Notes: The table shows the IV coefficients obtained by running 2SLS on equation (9). Dependent variable: *Markups*$_{it}$ indicates firm-level markups following De Loecker and Warzynski (2012). *Intangibles*$_{it}$ indicates (the log) firm-level intangible assets from the 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 treatments with a post-change in policy variable. In columns 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 columns 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, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

ically through the financing of intangibles. To address the endogeneity concern discussed above, we adopt an instrumental variable strategy that uses the policy shock as an instrument for intangible expenditure. We consider the following specification:

$$\ln \mu_{it} = \alpha + \beta \ln Y_{it} + c_i + \delta_t + \epsilon_{it} \tag{9}$$

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 (9), instrumenting intangibles with the liquidity shock. Specifically, we use $Post_t \times T_{j,it}$ as an instrument for Y_{it} while including the same set of controls for liquidity as in the main estimating equation (7).

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 well exceeding the Stock and Yogo (2005) rule-of-thumb cutoff of 10 in all specifications.

The results in columns (1) and (2) suggest that after a 10% increase in intangible capital, a firm's price-cost margin widens by about 3%. Similarly, columns (3) and (4) show that increasing spending on intangibles by 10% leads to an increase in price-cost margins by about 5%. Results are largely robust to different definitions of the treatment group and measure of intangible capital (columns (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.

Robustness Figure A.4 in the Appendix presents a battery of robustness checks for our estimates of β. We examine how β changes when: (i) changing the set of controls by incorporating firm sales and productivity and considering time-invariant controls interacted with the Post dummy, as well as time-varying controls; (ii) considering alternative definitions of the markup variable as described in section 3; (iii) examining 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 all estimates of β are positive and statistically significant, with the majority falling between 0.2 and 0.5. Our preferred estimate is largely within all confidence intervals. We also report the F-stat for all specifications, which shows a strong instrument in all cases.

Finally, Table A.6 in the Appendix demonstrates that the findings hold when considering alternative indicators of competitive advantage, such as market shares and sales (both total and international).

4.4 Testing the Exclusion Restriction

So far, the evidence backs our hypothesis that the availability of short-term financing is a source of competitive advantage by enabling investments in intangibles. The assumption that intangible investment is the sole channel through which liquidity influences competitive advantage also underpins the instrumental variable strategy discussed in section 4.3. However, it's possible that changes in trade credit regulations might impact other business decisions, not just intangible investments, which could also confer a competitive edge.

For instance, a firm's productivity and its marginal cost, which affect its ability to set high price-cost margins, may be influenced by investments in physical capital, such as machinery

Table 5: Exclusion Restriction Test: Alternative Channels

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimation:	DiD OLS							
	Tangible Capital				*Borrowing Capacity*			
Dep. Variable:	ln Fixed Assets $_{it}$		ln Tangible Assets$_{it}$		ln LongDebt$_{it}$		DTA$_{it}$	
T$_{1,it}\times$Post$_t$	-0.002		0.008		0.026		0.005***	
	(0.012)		(0.015)		(0.022)		(0.002)	
ln (1+T$_{2,it})\times$Post$_t$		-0.002		-0.000		0.001		0.001**
		(0.003)		(0.004)		(0.006)		(0.001)
Observations:	1,014,604	1,009,184	757,256	753,124	570,772	567,904	1,017,464	1,012,040
R-squared:	0.933	0.933	0.928	0.928	0.761	0.761	0.602	0.603
Fixed Effects:	Firm; Year				Firm; Year			

Notes: The table shows DiD coefficients obtained by running OLS on equation (7). The dependent variable in columns (1)-(2) is the (log of) firm-level tangible assets (from balance sheet); it is the (log of) firm-level long-term debt (from balance sheet) in columns (3)-(4); and, lastly, it is the firm-level debt-to-assets ratio in (5)-(6) (computed from balance sheet data). $T_{1,it}$ is the treatment variable defined in equation (5), 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 (6), 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, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

or automation technology. The relaxation of liquidity constraints could have led to increased investments in these assets, resulting in higher markups. Moreover, the reform may have enhanced the borrowing capacity of treated firms, allowing them to consolidate and expand their pricing power. Additionally, the reform might have strengthened a firm's bargaining power by making payment terms more favorable, leading to increased markups.

To investigate whether the trade credit reform impacted markups through alternative channels, we adapt our methodology to estimate equation (7) using a different set of dependent variables. Specifically, we consider: (i) physical capital, measured either as total fixed assets (Fixed Assetsit) or tangible fixed assets (Tangiblesit); and (ii) the firm's borrowing capacity, indicated by either reported long-term business debt (LongDebtit) or the business leverage, i.e., the debt-to-asset ratio (DTAit).[20] This additional analysis aims to determine if the trade credit reform may have influenced firms' competitive advantages through channels other than intangible assets.

The results are presented in Table 5. We find that the trade credit reform did not significantly affect the measures of physical capital or long-term business debt. The reform did cause a marginal increase in the debt-to-asset ratio of treated companies, but the effect

[20] It is important to note that a firm's borrowing capacity might also be correlated with its physical capital investment, as the latter frequently serves as collateral for loans, which can influence borrowing capabilities.

size was minimal. We further confirmed that such changes in the debt-to-asset ratio had no significant impacts on intangible investment or markups by including DTA_{it} as a control variable in our main analyses.[21] These findings support our hypothesis that the reform did not differentially affect the physical capital, borrowing capacity, or bargaining power of treated versus non-treated firms. This leads us to conclude that intangible assets play a crucial role in understanding the connection between liquidity constraints and markups.

5 Concluding Remarks

This paper explores the relationship between short-term financing, specifically trade credit, intangible investments, and competitive advantage. An analysis of a policy reform in France that induced quasi-experimental variations in liquidity across firms demonstrates that liquidity constraints significantly impact a company's ability to finance intangible assets. It also shows that firms that invest more in intangibles can charge higher markups over marginal costs. These findings underscore the importance of liquidity constraints as a critical factor influencing the different levels of intangible investments across firms and shaping their competitive advantages.

The study highlights the significant role financial factors play in enabling firms to invest in intangible capital and secure a competitive advantage, beyond mere productivity. It suggests that liquidity can be strategically leveraged as an asset to provide firms with a competitive edge. Furthermore, our findings indicate that financial conditions may have contributed to the emergence of "superstar" firms, characterized by substantial investments in intangible assets. This research reveals a channel through which financial factors impact the real economy and underscores the potential far-reaching benefits of enhancing national financial infrastructure to support firm growth and reduce resource misallocation.

We suggest several avenues for future research. First, while the research design offers insights into the differential effects of liquidity on investment among otherwise similar firms, it does not quantify the absolute importance of liquidity constraints. Future work could integrate financial frictions into a macroeconomic framework to assess the significance of

[21] The first stage results are presented in Table A.7, and the second stage results are in Table A.8. Both tables demonstrate that incorporating DTA_{it} as a regressor did not alter the size of the key coefficients of interest.

liquidity constraints on the aggregate level of investment and markups.

Moreover, delving deeper into the relative importance of financial conditions and other institutional differences across countries in determining the observed cross-country variations in intangible investment and markups could provide valuable insights. Understanding these cross-country variations will aid policymakers in developing targeted strategies to enhance investment in intangible assets and promote economic growth and competitiveness at both firm and national levels.

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A Additional Figures and Tables

Table A.1: Intangibles and Liquidity

	(1)	(2)	(3)	(4)	(5)	(6)
Estimation:	OLS					
Dep. Variable:	ln Intan_{it}			ln IntanExp_{it}		
Current Liabilities_{it}	0.223***			0.225***		
	(0.011)			(0.008)		
Cash Holdings_{it}		0.003			0.035***	
		(0.004)			(0.003)	
Accounts Payable_{it}			0.127***			0.214***
			(0.009)			(0.007)
Observations:	156,909	148,938	156,238	219,805	207,646	218,710
R-squared:	0.904	0.903	0.903	0.963	0.963	0.964
Fixed Effects:	Firm; Year					

Notes: OLS estimations. The dependent variable *ln* $\textit{Intan}_{it}$ 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* $\textit{IntanExp}_{it}$ indicates the log of Intangible Operating Expenses, measured as revenues minus production costs, operaing profits and depreciation. *Current* $\textit{Liabilities}_{it}$, *Cash* $\textit{Holdings}_{it}$, and *Debt to* $\textit{Suppliers}_{it}$ 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, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.2: Intangibles and Markup

	(1)	(2)
Estimation:	OLS	
Dep. Variable:	ln μ_{it}	
ln Intan_{it}	0.004**	
	(0.002)	
ln IntanExp_{it}		0.0735***
		(0.003)
Observations:	148,208	206,495
R-squared:	0.929	0.923
Fixed Effects:	Firm; Year	

Notes: OLS estimations. Dependent variable is firm-level markups following the methodology in Appendix B. All regressions include controls for a firm's Current Liabilities and Cash holdings. Standard errors are in parentheses and clustered at the firm level, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.3: Intangible Intensity Across Industries

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 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.

Table A.5: Liquidity and Competitive Advantage: Reduced Form

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimation:	DiD OLS [First Stage]							
Dep. Variable:	ln μ_{it}		Share$_{it}$		ln Sales$_{it}$		ln Exports$_{it}$	
T$_{1,it}\times$Post$_t$	0.017***		0.001***		0.014**		0.047*	
	(0.003)		(0.000)		(0.006)		(0.027)	
ln (1+T$_{2,it}$)$\times$Post$_t$		0.004***		0.000***		0.003*		0.014*
		(0.001)		(0.000)		(0.002)		(0.008)
Observations:	212,665	211,643	212,665	211,643	212,665	211,643	96,179	96,001
R-squared:	0.916	0.916	0.959	0.959	0.979	0.979	0.909	0.909
Fixed Effects:	Firm; Year							

Notes: The table shows DiD coefficients obtained by running OLS on equation (7). $T_{1,it}$ is the treatment variable defined in equation (5), 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 (6), 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, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.6: Liquidity and Competitive Advantage: Robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimation:	2SLS [Second Stage]							
	Competitive Advantage							
Dep. Variable:	ln μ_{it}		Share$_{it}$		ln Sales$_{it}$		ln Exports$_{it}$	
ln Intan$_{it}$ [T$_{1,it}\times$Post$_t$]	0.305***		0.013*		0.237*		0.096	
	(0.107)		(0.007)		(0.121)		(0.710)	
ln Intan$_{it}$ [ln (1+T$_{2,it})\times$Post$_t$]		0.338**		0.020**		0.223		0.429
		(0.136)		(0.010)		(0.141)		(0.953)
Observations:	152,368	151,728	152,372	151,732	152,372	151,732	75,135	75,028
Fixed Effects:	Firm; Year							
F-Stat:	53.15	37.36	58.25	41.73	58.25	41.73	11.06	6.86

Notes: The table shows DiD coefficients obtained by running OLS on equation (7). $T_{1,it}$ is the treatment variable defined in equation (5), 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 (6), 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, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.7: First Stage: Robustness

	(1)	(2)	(3)	(4)
Estimation:	DiD OLS			
Dep. Variable:	ln Intan_{it}		ln IntanExp_{it}	
$\text{T}_{1,it} \times \text{Post}_t$	0.051***		0.022***	
	(0.013)		(0.007)	
ln $(1+\text{T}_{2,it}) \times \text{Post}_t$		0.013***		0.007***
		(0.004)		(0.002)
DTA_{it}	0.253***	0.251***	-0.185***	-0.184***
	(0.030)	(0.030)	(0.021)	(0.021)
Observations:	152,368	151,728	212,653	211,631
R-Squared:	0.902	0.902	0.962	0.962
Fixed E�ects:	Firm; Year			

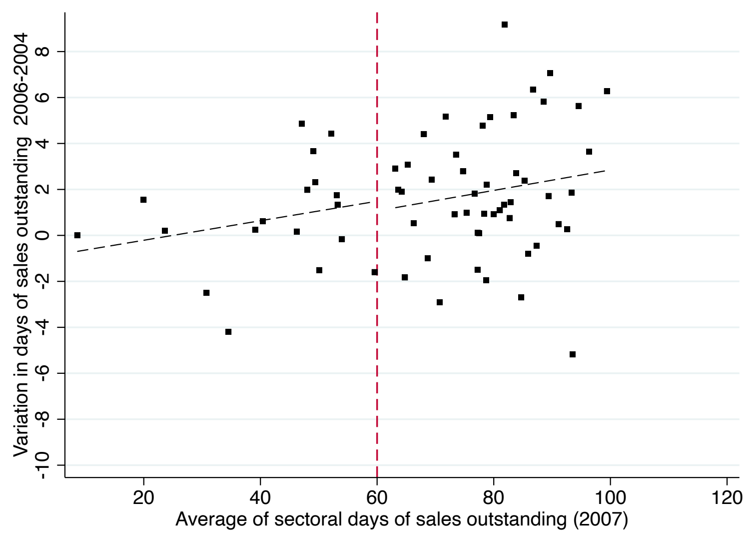
Notes: The table shows DiD coe�cients obtained by running OLS on equation (7). The dependent variable in columns (1)-(2) is the (the log of) firm-level intangible assets from balance sheet; it is total firm expenditure on fixed costs in columns (3) and (4). $T_{1,it}$ is the treatment variable defined in equation (5), 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 (6), 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 regressions include debt-to-asset leverage (DTA_{it}) as an additional control. All variables are deflated and expressed in 2010 Euros. All specifications include firm and year fixed e�ects. 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, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.8: Second Stage: Robustness

	(1)	(2)	(3)	(4)
Estimation:	2SLS			
Dep. Variable:	ln μ_{it}			
ln Intan$_{it}$ [T$_{1,it}\times$Post$_t$]	0.305***			
	(0.107)			
ln Intan$_{it}$ [ln (1+T$_{2,it})\times$Post$_t$]		0.338**		
		(0.136)		
ln IntanExp$_{it}$ [T$_{1,it}\times$Post$_t$]			0.785***	
			(0.284)	
ln IntanExp$_{it}$ [ln (1+T$_{2,it})\times$Post$_t$]				0.691***
				(0.256)
Observations:	152,368	151,728	212,653	211,631
Fixed Effects:	Firm; Year			
F-Stat:	53.15	37.36	41.64	42.90

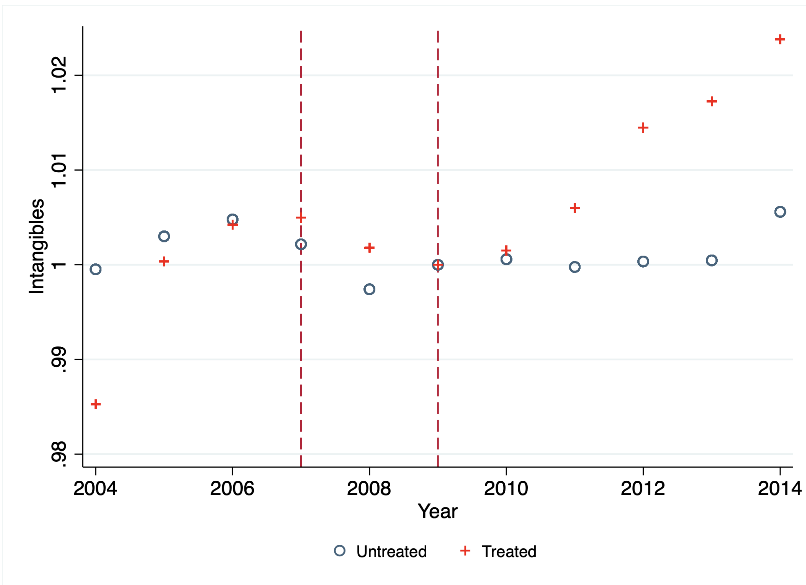
Notes: The table shows the IV coefficients obtained by running 2SLS on equation (9). Dependent variable: *Markups*$_{it}$ indicates firm-level markups following De Loecker and Warzynski (2012). Different rows correspond to different definitions of the treatment group in the first stage and different 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 treatments with a post-change in policy variables. 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 and the debt-to-asset leverage (DTA$_{it}$) as an additional control. 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, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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



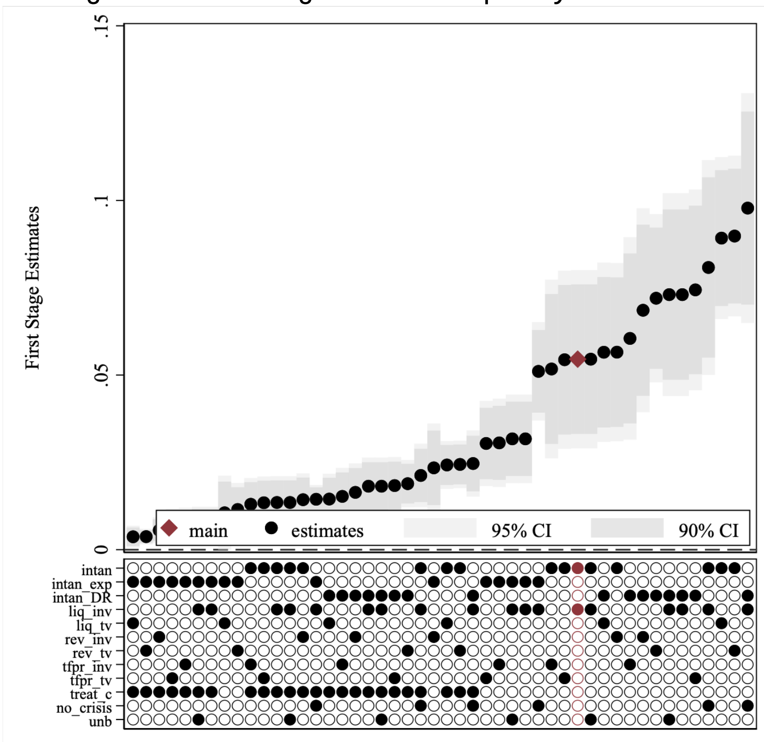
Notes: This graph displays the difference in days of sales outstanding between 2004 and 2006 as a function of the average DSO in 2004 for each NACE-4 digit industry. Since the years 2004 and 2006 were unaffected by the policy shock, we consider this figure as a placebo test of our measure of exposure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



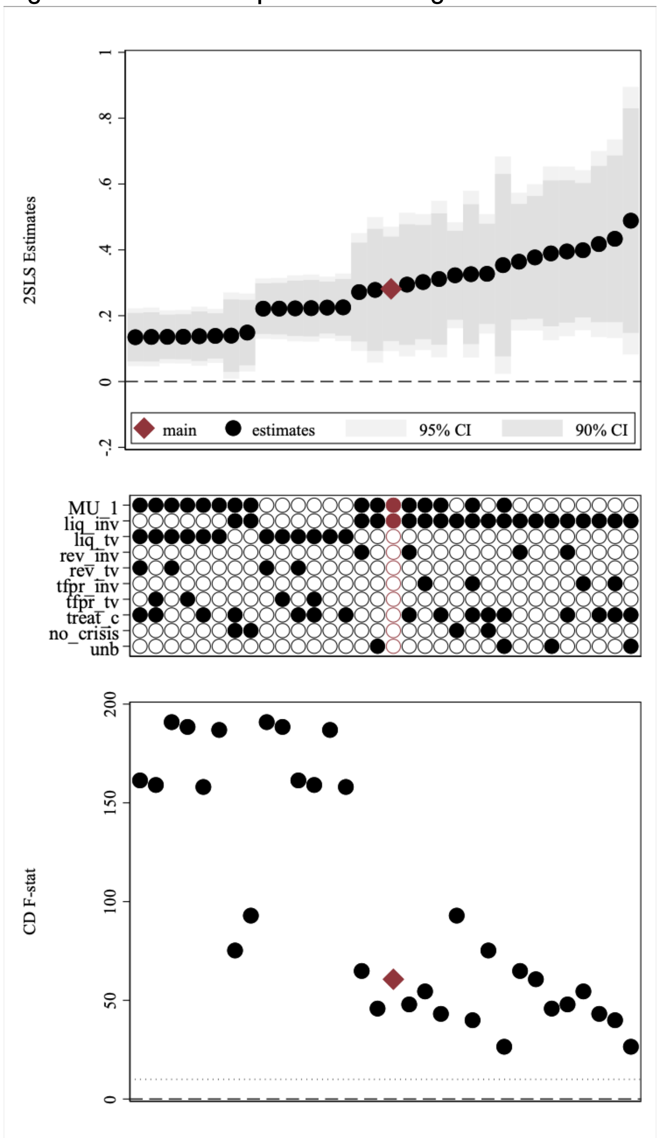
Notes: The graph shows trends (mean by year) in intangible capital (intangible assets) for both treatment and control group using the treatment definition T_1. The raw variables are normalized by the mean of treated and untreated firms in 2009.

Figure A.3: Intangibles and Liquidity – Robustness



Notes: The figure reports the estimates of β from 48 variations of regression equation equation (7). The dependent variable is the (log of) firm-level tangible assets (from the balance sheet), $\ln \mathrm{Intan}_{\mathrm{it}}$. 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 (2024). 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 specifications run 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 (9). Markups are regressed on the (log of) firm-level tangible assets (from the balance sheet), $\ln \mathrm{Intan}_{\mathrm{it}}$, instrumented by the liquidity shock. Each circle inside the main graph corresponds to the point estimate, with the 90% and 95% confidence intervals. The bottom of the graph indicates the features of each of the 32 specifications. 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-parameteric" 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 specifications run 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 the CD F-Stat for all specifications, which is always well exceeding the Stock and Yogo (2005) rule-of-thumb cutoff of 10.

B 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 2. Accounting for intangibles in the estimation of production functions has been shown to be important to avoid biases in the estimation of output elasticities and the estimation of both markups and productivity thereof (CompNet, 2020).

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

B.1 Production Function Estimation

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

$$Q_{it} = e^{\omega_{it}+\phi_{it}+\epsilon_{it}} F_t(K_{it}, \mathbf{V}_{it}; \beta), \tag{10}$$

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 $\mathbf{V}_{it}$.[22]

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 3, 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.

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

We thus write (10) in explicit form as:

$$\begin{aligned} q_{it} &= \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_{kk} k_{it}^2 + \beta_{ll} l_{it}^2 + \beta_{mm} m_{it}^2 + \\ &\quad \beta_{kl} k_{it} l_{it} + \beta_{lm} l_{it} m_{it} + \beta_k m k_{it} m_{it} + h(\omega_{it}, s_{it}) + \epsilon_{it}, \end{aligned} \tag{11}$$

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

As well-known in the literature, the estimation of (11) 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.*

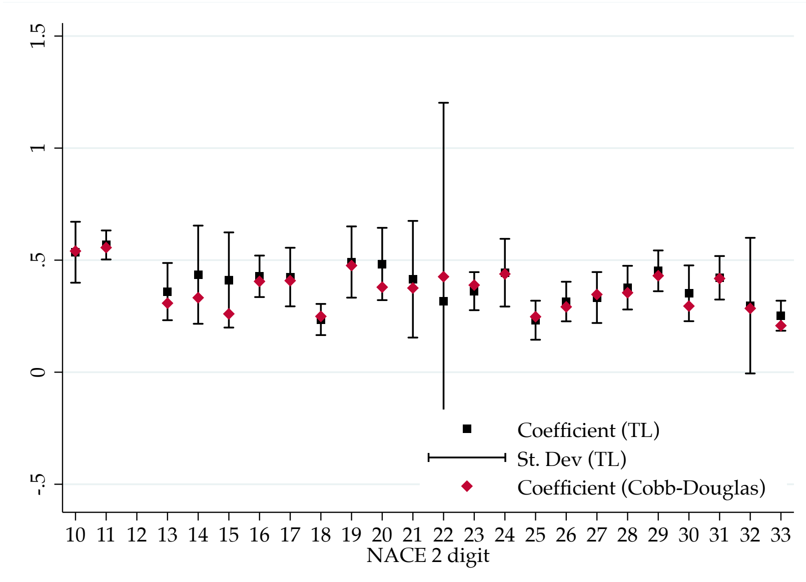
Under assumption A1, input quantities can be consistently measured as deflated expenditures, provided that exogenous differences in input prices across firms are not too large (De Loecker et al., 2016).

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:

$$\begin{aligned} r_{it} &= \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_{kk} k_{it}^2 + \beta_{ll} l_{it}^2 + \beta_{mm} m_{it}^2 + \\ &\quad \beta_{kl} k_{it} l_{it} + \beta_{lm} l_{it} m_{it} + \beta_k m k_{it} m_{it} + h(\omega_{it}, s_{it}) + \underbrace{p_{it} + \epsilon_{it}}_{u_{it}}, \end{aligned} \tag{12}$$

where u_{it} is the new error term that includes the unobserved output prices. Following the literature, we estimate (12) 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

Figure B.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.

imposing structure on the production process to identify the true parameters. The identifying restrictions are that the TFP process's innovation is not correlated with current capital and last-period variable inputs. These moment conditions are fully standard in the production function estimation literature.

Figure B.1 plots the estimates of the output elasticities of the material input from equation (12) 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 term $\widehat{h_{it} + p_{it}}$ as a residual of equation (12). This term reflects physical e□ciency and the average price of firm i, thus a measure of total factor revenue productivity.

B.2 Markups

Once we have estimated the main elasticities, we can 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 making assumptions on demand and how firms compete.

We consider the problem of a firm producing using technology as in (10) and choosing inputs to minimize variable costs. Under 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 (10), 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:

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