Three Essays in Empirical Corporate Finance

PhD Thesis

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Chapter 1

Preface

1.1. Introduction

My doctoral studies focus on empirically analyzing the factors that influence public and private firms' growth and efficiency strategies, with a particular focus on understanding the role played by institutional investors and financial intermediaries in these processes.

The motivation for my work stems from the rapid evolution of financial markets in recent years, which has significantly reshaped the capital structure of listed and private companies. To illustrate this, let's consider the example of index funds for public firms. The rise of index funds has given rise to the common ownership phenomenon, where large institutional investors hold blockholding positions in multiple competing companies. This development has far-reaching implications for corporate governance and the interconnectedness among firms, potentially facilitating spillover internalization processes and improving firm efficiency. On the other hand, private firms have been affected by the emergence of fintech platforms, which have facilitated retail investors' access to invest in private companies. This democratization of investment opportunities has the potential to impact firms' capital-raising strategies and access to funding, thereby influencing their growth trajectories. In my research, I aim to address essential questions: How do firms decide between pursuing growth and enhancing efficiency? How do these new trends in financial markets impact firms' strategies? Specifically, I focus on investigating whether passive common owners positively impact firms' efficiency. Additionally, I examine the potential of crowdfunding to alleviate capital constraints for small firms, thereby fostering growth.

Through rigorous empirical analysis and leveraging diverse datasets, I aim to unravel the intricate dynamics underpinning modern financial markets and their profound implications for firms' strategic choices and performance.

1.2. Summary of papers

Chapter 2, "Passive Common Ownership and Firm Markup: Marker Power of Efficiency?" explores whether passive common owners assist firms in internalizing spillovers by promoting the dissemination of information, thereby enhancing their efficiency. By using the addition of a competitor to the S&P 500 as exogenous shocks, I find evidence that passive common owners positively affect firm markups. This effect is particularly pronounced in industries with high technological spillover and good management practices, where the incorporation of information is more effective. The positive impact on markups results from improved firm efficiency, measured by variables like total factor productivity and investment efficiency. Importantly, this effect is not driven by firm market power exploitation, as there is no observed drop in R&D investment or output levels. Besides, by exploiting the engagement activity data of BlackRock, I underscore the significance of active engagement by passive common owners in the information dissemination process. This active engagement serves as a key mechanism through which the influence of passive common ownership shifts into firm policies. This research sheds light on a novel positive impact of common ownership in public markets.

Chapter 3, "How do Firms Choose between growth and efficiency?" (co-authored with Laurent Frésard, Loriano Mancini, and Enrique Schroth) studies the relationship between firms' growth and efficiency. To measure it, our approach treats productive efficiency as a deliberate choice made by firms, as opposed to taken as given by the firm and estimated as a residual. In our model, firms choose capital and labor jointly with effort to make these inputs more productive. Using this model, we estimate firms' unobservable efficiency effort from the data and find that young firms prioritize growth, while older firms focus more on efficiency. Over time, firms tend to shift their emphasis towards efficiency. Among young firms, those that pursue high growth tend to achieve higher markups, but also face a greater risk of failure. Our analysis sheds light on the factors that influence firms' growth and efficiency strategies and their implications. **Chapter 4, "Debt and Equity Crowdfunding in the Financial Growth Cycle"** (co-authored with Markus Lithell, Matteo Pirovano, and Trang Q. Vu) investigates firms' choice between issuing crowdfunded debt and equity and relate this to their stage in the financial growth cycle and access to bank financing. In particular, we focus on crowdfunded equity and debt issued in the US under Regulation CF of the JOBS Act. We find that firms that are less profitable, are in an earlier developmental stage, and have stronger ties to the banking system are more likely to issue crowdfunded equity than debt. Successful crowdfunding is associated with increases in firm size, revenue, and profitability for early-stage firms, but not for late-stage firms. Our findings are consistent with crowdfunding alleviating capital constraints and stimulating growth for early-stage startups, but having a negligible impact on established firms that are already profitable.

Chapter 2

Passive Common Ownership and Firm Markup: Market Power or Efficiency?*

Davide Sinno†

2.1. Introduction

Over the past years, passive investing has reshaped the landscape of the asset management industry and transformed the ownership structure of firms. A notable trend is the growing prevalence of common ownership, which occurs when the same institutional investor holds blockholding positions in multiple competing companies.‡ While common ownership has gained momentum, concerns have arisen regarding its potential anticompetitive effect. This perspective posits that common owners, driven by the pursuit of maximizing diversified portfolio returns, could deter firms from competing vigorously (Azar et al., 2018a). As a result, companies may exploit market power, driving up markups by setting high prices. However, the relationship between common ownership and firm markups is multifaceted. While higher markup indeed suggest market power, it can also reflect increased firm efficiency (Demsetz, 1973). In line with this, an alternative perspective emphasizes the role of common owners in promoting the exchange of information among the companies they invest in. This viewpoint suggests that common owners can enhance firm efficiency by facilitating the assimilation of information spillovers, particularly if a firm is well-positioned to absorb the information pro-

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‡For example, BlackRock is among the top 5 shareholders in Bank of America, Wells Fargo, J.P. Morgan and Citi Bank (Vives, 2019).

vided. This, in turn, leads to improved profit margins achieved through cost reductions rather than increased prices (López and Vives, 2019; Vives, 2019).

Despite evidence demonstrating the role of common owners in facilitating information exchange in private markets like venture capital (Eldar and Grennan, 2023), an unexplored aspect pertains to these dynamics within the public market, where common ownership is predominantly driven by passive investors. Contrary to the 'passive' label, these investors actively influence governance and company management (Appel et al., 2016, 2018) and have incentive to engage (Lewellen and Lewellen, 2021)[§]. In light of this active involvement, this study aims to fill this gap by investigating whether passive common owners, similar to their active counterparts in private markets, contribute to augmenting firm margins by facilitating information dissemination. Specifically, I examine whether the exchange of information among companies in their portfolios enhance firm efficiency, potentially leading to higher markups.

How do passive common owners facilitate the exchange of information? There are various mechanisms through which this can occur. In this paper, I will primarily focus on direct engagement with a company's board and management as a means of gathering information and sharing it across the firms within their investment portfolio. According to McCahery et al. (2016), a significant proportion of large institutional investors engage in discussions with management and hold private talks with the board. For instance, 63% of institutional investors engage in discussions with top management and 45% communicate with boards of directors independently from management. Passive investors have strong motivations for engagement. As the value of a portfolio company increases, it amplifies the total Assets Under Management (AUM) of the fund, leading to increased fees for the fund manager. The substantial direct incentives witnessed among major index asset managers are a result of a delicate equilibrium between fees and scale. Despite charging significantly lower management fees compared to actively managed funds, their extensive AUM and substantial ownership stakes can counterbalance the impact of these reduced fees (Lewellen and Lewellen, 2021).

An example of this engagement effort by index funds is the BlackRock Investment Stewardship (BIS) division. A Thomson Reuters article defines the BIS team as "one of the most influential forces in corporate America" and as "driving change behind the scenes on how companies run themselves".[¶] Through this engagement team, BlackRock acquires valuable insights into market trends, investment opportunities, and best practices.[‖] To maximize returns from their diversified portfolio, BlackRock leverage these insights to offer feedback on factors that can impact the future performance of these companies. While firms may eventually gain similar insights by observing their competitors, passive investors expedite and enhance this process through their proactive monitoring and engagement activity.

[§]"We are an active voice; we work with companies, but we need to work for the long-term interest. In my mind, activists are trying to improve the company, often in the short term, and then leave. We, as passive investors, are committed to long-term engagement." —Larry Fink, BlackRock CEO

[¶]Thomson Reuters Article

[‖]BIS teams documentation

To delve deeper into this phenomenon, my analysis begins by examining the impact of passive common ownership on firm markups, in industries characterized by varying levels of technological spillover and management practices. My underlying hypothesis posits that if passive common owners enhance markups through improved efficiency by facilitating spillover internalization, the effect will be stronger in industries with high technological spillover and good management practice. Firms in industries with high levels of technological spillover are expected to benefit more from internalizing information spillovers due to the higher degree of overlapping technologies (Vives, 2019). The concept revolves around the idea that information becomes more valuable when it originates from a company with a similar business model, as it can be directly applied to a firm's operations. Similarly, in industries characterized by well-established management practices, the internalization process is likely to be more effective. This is because companies with strong governance and better organizational capital tend to be more responsive and are better equipped to incorporate the new insights into their existing operational framework (Cohen and Levinthal, 1990). Besides, in these settings, passive investors are further incentivized to engage due to reduced costs. They benefit from economies of scope by aggregating information from one company and disseminating it across their portfolio. Additionally, well-managed companies facilitate more effective engagement for passive investors, as streamlined processes enable smoother interaction and fewer resource demands compared to firms with less efficient management structures (Rock and Kahan, 2018).

Next, I proceed to directly investigate whether the influence of passive common ownership on firm markups can be attributed to enhanced efficiency. I achieve this by analyzing the impact on two key indicators: total factor productivity (TFP) and investment efficiency. Additionally, I explore the market power narrative by examining the effect of passive common ownership on output and research and development (R&D) levels. According to the market power hypothesis, common ownership is expected to have a negative effect on investment and output, reflecting the reduced competitive pressure. In contrast, the efficiency story suggests a positive effect on productivity and investment efficiency, as firms internalize information spillover.

Finally, I examine the role of direct engagement by passive investors as mechanism in facilitating information dissemination and supporting the spillover internalization process. I utilize hand-collected data on the engagement activities of the BlackRock Investment Stewardship (BIS) team.[**] My analysis aims to determine whether engagement by the BIS team correlates with higher firm markups and improved efficiency, particularly in sectors characterized by high technological spillover and strong management practices—those where firms are well-positioned to absorb the insights provided by these teams.

I build on Anton et al. (2022) and Boller and Morton (2020) to address endogeneity and reverse causality concerns. I employ a difference-in-differences framework centered around

[**]In 2022, the BIS teams engaged with 2,069 firms. 520 companies have been engaged multiple times in the year (BIS teams documentation).

the inclusion of a competitor in the S&P500 index. The treated group comprises firms that belong to the same 4-digit Standard Industrial Classification (SIC) industry as the added firms and are already members of the S&P500. On the other hand, the control group consists of companies that are part of the S&P500 but operate in different 4-digit SIC industries than the added firms. As highlighted by Boller and Morton (2020), this identification strategy provides a means to differentiate the impact of an increase in common ownership from that of institutional ownership. Their findings indeed show that, following the addition of a competitor, treated firms experience an increase in common ownership while institutional ownership remains unchanged. This methodology allows to tackle some of the concerns related to the other shocks used in the common ownership literature (Lewellen and Lowry, 2021).

I find that passive common owners have a positive impact on firm markups, in industries characterized by high technological spillover and strong management practices. When a competitor is added to the S&P500, treated firms in high technological spillover industries experience a significant 3% increase in markups, while those in high management practice industries see a notable 2% increase. However, no significant effect is observed in sectors with low technological spillover and low management practice. These results align with the initial hypothesis and provide compelling evidence that passive common owners contribute to higher firm markups by facilitating the process of spillover internalization. This, in turn, leads to improved efficiency and ultimately higher margins for the firms.

In line with the efficiency narrative, I find that passive common owners have a positive impact on firms' TFP. After the addition of a competitor to the index, treated firms witness a rise in TFP of approximately 3% in high technological spillover industries and 2% in high management practice sectors. Similarly, in industries marked by strong management practices, passive common ownership contributes to a reduction of investment distortion (either underinvestment or overinvestment) by 2.2%, signifying an improvement in investment efficiency. While, in contrast to the market power hypothesis, I do not find negative impacts on firms' R&D or output levels. This supports the idea that the observed increase in markups is driven by improved efficiency rather than market power exploitation.

Finally, I show that the engagement activities of the BlackRock Investment Stewardship (BIS) team are positively associated with higher markups, TFP and investment efficiency in high technological spillover and strong management practices sectors. This highlights the pivotal role of active engagement by passive common owners in disseminating information and promoting the internalization of information spillovers and managerial insights.

In summary, this paper provides compelling evidence in favor of a previously unexplored positive aspect of common ownership in the public market. By facilitating the exchange of information among firms, passive common owners contribute to improved firm efficiency and, consequently, higher profit margins. This efficiency-driven hypothesis is substantiated by the positive impact of common ownership on total factor productivity (TFP) and investment efficiency. It's worth noting that this effect is distinct from the promotion of market power exploitation, as evidenced by the absence of any observed decline in R&D investment and output levels.

My results are robust to various checks and alternative specifications. Firstly, I establish that the inclusion of a competitor in the S&P500 index acts as a shock specific to quasi-indexer investors, while having no impact on the level of common ownership from active investors. Secondly, by examining the removal of a competitor from the S&P500 as a negative shock to common ownership, I find no effects on markups and productivity, as no spillover effect is involved in such cases. Thirdly, the results remain robust when using different definitions of technological spillover and management practice, employing variables such as knowledge and organizational capital (Peters and Taylor, 2017a). Lastly, the findings hold even when using an alternative definition of markups, which considers operating expenses adjusted by R&D and RDIP as variable costs, accounting for selling, general, and administrative expenses (SG&A) more accurately than the cost of goods sold (COGS) (Ayyagari et al., 2023; Traina, 2018).

My paper contributes to different strands of the literature. It complements existing research on the positive aspects of common ownership. Recent studies have highlighted its potential to foster innovation (Li et al., 2023; Anton et al., 2017). Besides, common ownership has been found to facilitate collaboration among firms, whether through direct product market interactions (He and Huang, 2017) or more subtle mechanisms such as easing information spillover internalization (Vives, 2019). Empirical evidence by Eldar and Grennan (2023) shows that venture capital common ownership supports the growth of private firms by facilitating information sharing. I add to this research by offering empirical evidence that passive common owners in the public market also play a role in facilitating the exchange of information among companies, which subsequently leads to improved firm efficiency.

My work also establishes a connection among the divergent findings between common ownership, competition dynamics, and firm outcomes. Common ownership has been suggested to reduce firms' incentives to compete, as observed in the airline industry (Azar et al., 2018a). While a debate is still ongoing on this effect (Dennis et al., 2022; Azar et al., 2018b), Koch et al. (2020) found limited evidence of correlations between common ownership and industry profit margins. My research reveals a positive effect of common ownership on firm markups at the firm level. Importantly, this outcome is not a result of common owners facilitating firms in exploiting market power; instead, it stems from the enhancement of firm efficiency. This effect, however, holds true only when a firm is well-positioned to internalize the information shared by these investors.

Next, my study contributes to the recent studies on the relationship between star firms and market power. Star firms have been linked to various trends in the economy, such as a decline in investment in physical capital, a rise in market concentration, and a decrease in the labor's share (Gutiérrez and Philippon, 2017; Grullon et al., 2019; Barkai, 2020). An ongoing debate concerns whether the rise of star firms is due to their ability to exploit market power (Grullon et al., 2019; De Loecker et al., 2020a) or to differences in productivity and efficiency (Crouzet and Eberly, 2018; Ayyagari et al., 2023; Autor et al., 2020). The recent literature attempts to establish a connection between common ownership and the superstardom trend. My results indicate that if such a connection exists, passive common owners may corroborate star firms' market power, contributing to their efficiency level rather than facilitating anti-competitive behavior.

Lastly, my findings enhance the existing research on institutional ownership and governance. Prior studies highlight the substantial impact of institutional investors on shaping corporate governance and influencing company policies (Aghion et al., 2013). Also passive investors assume a role that extends beyond their "passive" label, actively influencing firms' management strategies (Appel et al., 2016, 2018). In alignment with this, He et al. (2019) show that passive investors' active engagement in corporate governance is motivated by their cross-holding positions, incentivizing them to monitor and incorporate governance practices. Similarly, Edmans et al. (2018) propose that the association between common ownership and higher prices may arise from improved governance practices, ultimately resulting in elevated product quality and pricing efficiency. In this context, my research adds a novel dimension by emphasizing the role of passive common owners in influencing and enhancing firms' governance practices through information dissemination. Additionally, I highlight a key way through which common ownership affects outcomes: active engagement. This finding adds to the existing research on how common ownership translates into firm policies (Anton et al., 2022).

The paper is organized as follows. Section 2.2 outlines the methodology used to measure common ownership and firm markups. It also provides an overview of the data sources used, including information on BIS engagements, technological spillovers, and management practices. Section 2.3 presents the economic argument that underlies the testable hypotheses regarding the relationship between common ownership, markups, managerial knowledge, and technological spillovers. This section concludes with exploratory panel regressions to provide initial insights. Section 2.4 discusses the identification strategy, which is based on a Difference-in-Differences framework centered around the inclusion of a competitor in the S&P500 index and it presents the main results for firm markups. Section 2.5 focuses on the efficiency versus market power hypothesis by analyzing the effect of passive common ownership on TFP, investment efficiency, output and R&D. Additionally, this section explores the role of engagement by passive investors in facilitating the internalization of spillovers. Section 2.6 includes a set of robustness tests while Section 2.7 concludes.

2.2. Data and motivation

2.2.1. Institutional ownership and investor classification

Institutional ownership data comes from Thomson Reuters Institutional Holdings Database. The primary source of this dataset is the 13F form that investment companies and professional money managers file with the SEC quarterly. To proxy institutional investors' activity, I calculate the institutional ownership ratio by dividing the level of institutional ownership by the total shares outstanding. Institutional ownership ratios sometimes can be greater than one. This data issue is related to the fact that 13F data only include long positions; however, it is a minor concern since less than 1% of firms present values higher than one. I winsorize institutional ownership to a maximum of 1.

Following Bushee (1998, 2001), I categorize institutional owners into three groups based on their portfolio characteristics of turnover and diversification: 'dedicated' (DED), 'transient' (TRA), and 'quasi-indexers' (QIX). Dedicated institutional investors have low portfolio turnover, maintain a significant stake in a few firms, and have a long-term investment horizon. They have been found to be associated with firm innovation (Aghion et al., 2013). Transient owners have high portfolio turnover and maintain diversified portfolio holdings, which aligns with short-term investment strategies like momentum. Finally, quasi-indexers are passive investors with diversified holdings and exhibit low portfolio turnover.

Figure 2.1 shows that the increase in average institutional ownership is primarily driven by the emergence of quasi-indexer investors, whose ownership increases from 12% to almost 30%. Transient ownership also rises from 5% to 15%, while dedicated ownership remains stable at around 5%. The growing popularity of passive investing can be attributed to its lower fees and simplified investment approaches, resulting in a surge in the number of quasi-indexer funds from approximately 480 in the 1980s to more than 2500 today, as shown in Figure 2.A.1, which explain the increasing presence in the firms'equity.

2.2.2. Passive Common ownership

I define same-industry common-ownership as a firm sharing an institutional blockholder with a peer firm within its respective 4-digit SIC industry. Specifically, I focus on common ownership generated by passive common owners (QIX investors). To measure passive common ownership at the firm level, I construct the variable *N. Connections* which represents the number of unique same-industry peers that share any QIX common institutional blockholder. It is equivalent to *NumConnected* used in He and Huang (2017). The *N. Connections* provides an indication of the overall level of connectivity between a firm and its competitors through shared passive owners.

I only consider institutional blockholding positions with ownership greater than or equal to

0.5%. This threshold is consistent with previous studies (Azar and Vives, 2019; Borochin et al., 2018), and it ensures that only substantial institutional holdings are considered. A commonly used threshold to define a blockholder is 5%. However, in this study, institutional investors are categorized into different types, and using a 5% threshold may result in a limited number of observations, which could hinder drawing meaningful conclusions. Therefore, in this context, using a lower blockholder threshold may be more suitable to ensure an adequate sample size.

Figure 2.2 shows the evolution of common ownership over time. With the increasing popularity of passive investing, the number of quasi-indexer and transient common owners has significantly increased. On average, a firm today has 10 quasi-indexer and 4 transient unique common owners, compared to only 2 and 1, respectively, back in the 1980s.[††] Meanwhile, there is no variation in dedicated common ownership. This is not surprising, as passive investors tend to have more diversified portfolios compared to active investors.

2.2.3. BlackRock investment stewardship engagement

Passive investors, while not actively managing the companies they invest in, have several avenues through which they can exert influence on management decisions. They can participate in decision-making processes by exercising proxy votes, influence management through the exit option by threatening to sell shares, and engage in direct discussions with management or the company's board to express their opinions and concerns. One notable example is BlackRock's Investment Stewardship (BIS) division, which focuses on engaging with company executives, board directors, and other shareholders, as well as collaborating with the company's advisors to address governance and business practice issues.[‡‡]

To investigate how common ownership translates into firm policies, I collected data on the engagement activities of the BIS team from 2020 to 2022. Specifically, I recorded the number of times a firm was engaged by the BIS team within each year. This data enables me to measure the influence and effectiveness of passive investor monitoring on corporate decision-making processes and outcomes.

2.2.4. Markups

Markup is typically defined as the ratio of output price to marginal cost. One possible way to estimate markups is through the production approach, which derives markups from a firm's cost minimization decision. In a recent study, De Loecker et al. (2020a) use this method to estimate firm-level markups. This approach utilizes publicly available accounting data, eliminating the need for assumptions on demand and competition among firms. The final markup expression is obtained by exploiting cost minimization of a variable input of production. This method has two advantages: it allows for the derivation of a markup measure at the firm level, and it relies

[††]This finding is consistent with Elhauge (2016).
[‡‡](BIS teams documentation - Page 6)

on accessible accounting data for estimation. The final expression is:

$$\mu_{it} = \theta_{it}^{v} \frac{P_{it} Q_{it}}{P_{it}^{V} V_{it}} \tag{2.1}$$

Where P_{it} is the output price, Q_{it} is the total output, P_{it}^{V} is the input price and V_{it} is the total input. The two ingredients to compute the markup are the revenue share of the variable input, $\frac{P_{it} Q_{it}}{P_{it}^{V} V_{it}}$, which is directly observable in the data, and the output elasticity of the variable input, θ_{it}^{v}, which is estimated from a single input production function.

Figure 2.3 shows the evolution of the aggregate markup over time. The average markup has risen from 15% in the 1980s to 40% today. The surge is primarily driven by firms in the upper tail of the distribution. This suggests that a small group of companies, commonly referred in the literature as "star firms," is experiencing a faster increase in markup than the rest of the economy.[§§]

There are varying opinions on the relationship between star firms and markups. One perspective suggests that the rise in markups is explained by the ability of star firms to exploit market power and follow a strategy of high markup, low output, and low investments (Gutiérrez and Philippon, 2017; Grullon et al., 2019). Another interpretation links markups to the greater efficiency of these firms, primarily resulting from previous investments in R&D (Crouzet and Eberly, 2018; Ayyagari et al., 2023; Autor et al., 2020). Recent empirical evidence suggests that common ownership may play a role in explaining this trend. Common owners reducing the competitive pressure among firms in their portfolio may allow these stars to exploit market power (Azar et al., 2021, 2018a). On the other hand, theoretical works highlight that common owners may increase firms' efficiency, aligning with the second perspective (López and Vives, 2019; Vives, 2019).

2.2.5. Technological spillover

There is ample empirical evidence supporting the existence of R&D spillovers. However, one issue with this research is that R&D can generate two types of spillover effects, namely "Technology spillovers" and "Product market rivalry". The former type is beneficial for firms operating in the same technological area, as it enhances their productivity. For example, Apple and Samsung had a positive early-stage relationship where Samsung supplied components to Apple, benefiting both firms. In contrast, the latter type of spillover can harm a firm's performance due to the stealing of business opportunities. A notable instance of this is the 2011 patent infringement lawsuit filed by Apple against Samsung. I am primarily interested in the "technology spillover" measure because common owners, in order to maximize their portfolio returns, encourage cooperation among firms in their portfolio and facilitate the internalization of R&D

[§§]Examples of such firms include tech giants like Google, Amazon, and Apple, as well as non-tech companies such as Nike and Coca Cola.

spillovers by promoting the spread of information across firms (López and Vives, 2019).

Bloom et al. (2013) develop a methodology to disentangle the two types of spillover. Technology spillover for firm i in year t is:

$$\text{SPILLTECH}_{it} = \sum_{i \neq j} TECH_{ij} G_{jt} \tag{2.2}$$

$TECH_{ij}$ is the firm's position in the technology space, which serves to assess the technological proximity to the main competitors. Higher proximity to another firm increases the probability to benefit from each other R&D. This is computed as the uncentered correlation of the share of patent in each technological classes between all firms i, j pairings. This index ranges between 0 and 1, depending on the degree of overlapping technology. G_{jt} is the stock of R&D investments of rival firms. The firm-level measure of technology spillover is therefore a sum of rivals' R&D stock weighted by the degree of overlapping technology. In this paper, I use the spillover measure computed using the Mahalanobis distance metrics which account for spillover in different technology classes (Bloom et al., 2013).

2.2.6. Management practices

Bloom and Van Reenen (2007) introduce a novel survey methodology for assessing management practices. They employ an interview-based evaluation tool that assigns scores ranging from 1 (representing the poorest practice) to 5 (representing the best practice) for 18 fundamental management practices. A score of 5 means that a firm has adopted a practice that results in a productivity increase. The survey employs a "double-blind" technique, which involves two aspects. Firstly, the managers being interviewed are not informed that they are being scored. Secondly, the interviewers are not provided with any prior information about the firms' performances. This ensures that the results are not biased and accurately reflect the practices in place. The management practices are divided into 4 broader areas: 1) *operation* - do companies introduce new lean modern technique? 2) *monitoring* - how well do companies monitor what goes on inside their firms and use this for continuous improvement; 3) *targets* - do companies set the right targets, track the right outcomes, and take appropriate action if the two are inconsistent? 4) *People* - are companies promoting and rewarding employees based on performance, and trying to hire and keep their best employees? The study focuses on medium-sized manufacturing firms employing between 100 to 5000 workers. The authors conducted interviews from 2004 to 2015 with more than 10,000 firms in 35 countries, mainly private companies. To ensure consistency with my sample of U.S. listed companies, I use data on management practices from firms with headquarters in the U.S. and more than 500 employees. Small companies are excluded from the analysis because their practices may differ significantly from those of large listed firms.

2.2.7. Summary statistics

The starting sample includes all publicly traded U.S. firms from Compustat. I exclude financial services firms (SIC codes 6000 to 6999), utilities (SIC codes 4900 to 4999), and regulated firms (SIC codes 8000 to 9999). Consistent with Ayyagari et al. (2023), observations with negative values for employees, sales, total assets, current assets, current liabilities, fixed assets, cash, goodwill, as well as those with missing total assets, sales, or SIC codes, are dropped. Table 2.1, Panel A, presents the summary statistics for the technological spillover sample. The sample spans from 1980 to 2018. Panel B reports the summary statistics for the management practice sample, which is available only for the manufacturing sector and starts from 2004.

To calculate the technological spillover for each industry j, I use firm-level data from Bloom et al. (2013). Each firm's technology spillover is computed as the median spillover value during the sample period. Industry j's technology spillover is then determined as the cross-sectional median of all firms' technology spillover within a given two-digit SIC industry. Similarly, industry j's management practice is calculated as the cross-sectional median of all firms' management practices within a given two-digit SIC industry. Table 2.A.2 presents the level of technological spillover and management practices for each industry.

2.3. Passive common owners and spillover internalization

2.3.1. Economic argument

How do passive common owners influence firms' markups? Value maximization should be all firms' goals. However, if shareholders own diversified portfolios do not want value maximization to be a corporate policy. Instead, they want a policy of portfolio value maximization, more specifically, a policy of internalization of between-firm externalities (Hansen and Lott, 1996). Fierce competition among firms can generate negative externalities that diminish the returns on a diversified portfolio. Consequently, common owners have an incentive to mitigate rivalry among their portfolio firms and promote implicit or explicit cooperation (He and Huang, 2017). Similarly, Vives (2019) argues that common ownership, by encouraging information sharing, enables firms to internalize corporate spillovers, resulting in enhanced efficiency, reduced production costs, and higher markups.

Passive investors, as highlighted in the BlackRock Investment Stewardship report, gain insights on investment opportunities, management practices, and strategies through their engagements with diverse firms. Their diversified portfolios grant them a unique advantage, facilitating access to extensive market-wide information (Rock and Kahan, 2018; Brav et al., 2023). Driven by goals of portfolio optimization, they have incentive to share valuable information acquired from one company with others.

Based on this premise, I have formulated two hypotheses. Firstly, I posit that the information flow facilitated by passive common owners could significantly benefit firms operating in industries characterized by high levels of technological spillover. In these sectors, the information exchange could be particularly advantageous because it occurs among companies with very similar businesses and products (López and Vives, 2019; Vives, 2019). Additionally, passive investors are more inclined to engage and sustain the flow of information due to the potential for economies of scope. By collecting information from one company and sharing it with others, their engagement becomes more cost-effective (Rock and Kahan, 2018). As a result, this information flow facilitates the internalization of information spillover, enhancing efficiency within firms. This, in turn, is anticipated to have a positive impact on markup rates.

Secondly, I argue that this information exchange is especially beneficial for firms with strong management practices. This hypothesis is grounded in the notion that companies with robust management capabilities are better equipped to absorb and integrate new insights into their existing operations. Their superior organizational capacity facilitates the internalization of new information, subsequently enhancing their operational efficiency and profit margins (Cohen and Levinthal, 1990). Consequently, the incentive for passive investors to engage with well-managed companies is higher due to the lower cost[¶¶] (Rock and Kahan, 2018). In summary, if passive common owners contribute to boosting firms' markups by facilitating the internalization of information spillovers, thereby enhancing their efficiency, these effects are likely to be more pronounced in industries characterized by:

1. Industries with high level of technological spillover.

2. Industries with better management practices.

2.3.2. Preliminary analysis

As a preliminary test, I estimate the following model:

$$\text{Log Markup}_{i,t+1} = \alpha + \beta \text{N. Connections}_{it} + \gamma \text{Z}_{it} + \lambda_j + \tau_t + \varepsilon_{it} \qquad (2.3)$$

The dependent variable is a firm's one year-ahead markup in logarithmic form, *N. connections* proxies passive common ownership for firm i in year t as described in the previous section. Z_{it} is a vector of control variables. I include industry fixed effect λ_j and year fixed effect τ_t. Standard errors are clustered at the firm level. To test my hypothesis, I divide the sample into two groups. The first group includes firms in 2-digit SIC industries with high technological spillover, determined by comparing the technological spillover to the median value.

[¶¶]The costs associated with engagement are multifaceted and encompass various aspects. These include expenses related to acquiring information, direct costs involved in engagement activities like the time and effort dedicated to communication and negotiations, legal expenditures, disclosure costs, filing expenses, as well as hiring professionals such as proxy solicitors, governance experts, and public relations firms. Additionally, there are indirect costs associated with engagement, such as potential reputational repercussions (Brav et al., 2023; Rock and Kahan, 2018) associated with such engagements.

The second group includes firms in 2-digit SIC industries with low technological spillover. Additionally, I split the sample into two groups based on the median management practice, where one group comprises firms in industries with high management practice and the other group comprises firms in industries with low management practice.

Table 2.3 presents the estimation results for Eq. 2.3. Column (1) includes the results for the full sample, column (2) the results for firms in industries with low technological spillover, and column (3) the results for firms in industries with high technological spillover. In Column (1), the coefficient of *N. Connections* is positive and statistically significant at the 5% level. This suggests that an increase in passive common ownership has a positive impact on firms' markup in the following year in the overall sample. However, when I split the sample into low versus high technological spillover industries, I observe a more nuanced pattern. In line with hypothesis (1), in industries with high technological spillover (Column 3), common ownership significantly bolsters firm markup. On the other hand, in industries with low technological spillover (Column 2), the coefficient is not statistically significant. In term of economic magnitude, I estimate that a one standard deviation increase in *N. Connections* corresponds to a 3.5% increase in markups for firms in industries with high technological spillover.

Columns (4) to (6) of Table 2.3 report the results for management practice. Column (4) represents the estimates for the full sample, column (5) corresponds to firms in industries with low management practice, and column (6) corresponds to firms in industries with high management practice. Consistent with hypothesis (2), the coefficient of *N. Connections* is positive and statistically significant at 5% level for firms in industries with good management practice (column 6), indicating that an increase in passive common ownership has a positive impact on firms' markup in these industries. Specifically, a one standard deviation increase in *N. Connections* corresponds to a 8.4% increase in markup. However, in industries with low management practice (column 5), the coefficient is not statistically significant.

Overall, these preliminary findings provide support for the idea that passive common owners play a critical role in facilitating the dissemination of information. When a firm is well-positioned to absorb these spillovers, it translates into higher markups. However, it is important to acknowledge the potential presence of endogeneity and reverse causality in the obtained results. I address this concern in the next section.

2.4. Identification strategy

One potential issue that can arise in the analysis is endogeneity, specifically concerning omitted variables that are correlated with both a firm's common ownership and its future markup. This correlation could introduce bias into the results and undermine the causal interpretation. Additionally, I need to account for the possibility of reverse causality, where firms with higher markups may attract more institutional crossholders. In this section, I address potential endogeneity problems by using a novel identification strategy: a Difference-in-Differences approach based on the addition of a competitor to the S&P500 as quasi-natural experiment that generates plausibly exogenous variation in a firm's common ownership.

2.4.1. S&P 500 competitor addition as exogenous shock

The literature proposes several instruments to estimate the impact of common ownership at the firm level, such as the BlackRock-BGI merger, institutional mergers, the Russel-index reconstitution, and the addition of a firm to the S&P500. However, these shocks have been widely criticized (Lewellen and Lowry, 2021). To address possible concerns, I employ a novel identification strategy proposed by Boller and Morton (2020) and recently extended by Anton et al. (2022). I use the addition of a stock to the S&P500 as an exogenous shock to the passive common ownership of its industry competitors that are already in the S&P500. When a firm is added to the S&P500, passive investors buy this stock to track the index, leading to an increase in common ownership for firms already in the index and within the same industry as the newly added firm. This identification strategy overcomes the primary criticism of using the addition of the firm itself as a shock to common ownership, which is the difficulty in distinguishing the effects of common ownership from those of institutional ownership. The addition of a stock to the S&P500 does not result in any change in the ownership of the index incumbent competitors, their institutional and block ownership remains unaffected, as noted by (Boller and Morton, 2020).

In Table 2.A.3, the variable *S&P500 competitor addition* is a dummy variable that takes the value 1 if any of the firms' competitors in the same 4-digit SIC industry has been added to the S&P500 in a given year, and 0 otherwise. Column (3) shows that following the inclusion of competitors in the S&P500, the number of connections for firms already in the index increases by 5%. Column (4) indicates that the level of institutional ownership remains unaffected. However, when controls are added, the addition has a negative and significant impact (Column 5 and 6). I estimate that if a firm is treated, it experiences a decrease in institutional ownership of 1% relative to the unconditional mean. This could be attributed to movement from institutional investors who sell shares due to potential increases in competition or reallocate capital toward the new entrant. Overall, the results indicate that treated firms experience an increase in common ownership following the treatment without positively affecting their institutional ownership.

2.4.2. DiD analysis

In order to assess the impact of additions to markups, I employ a difference-in-differences (DiD) framework that compares changes in markups before and after the addition. The analysis covers a period of eight years, four years before and four years after the addition. I identify as treated firms those that belong to the same 4-digit SIC industry as the added firms and are already members of the S&P500. For the control group, I select firms that are part of the S&P500

but operate in different 4-digit SIC industries than the added firms. To test hypothesis (1) and (2), I divided the treatment group into firms in industries with high versus low technological spillover and high versus low management practice. I identify 938 additions between 1980 to 2016, but only 398 with sufficient pre and post period. My baseline DiD model is:

$$\text{Log Markup}_{itd} = \beta_0 + \beta_1 \text{Treat}_{id} + \beta_2 \text{Post}_{td} + \beta_3 (\text{Treat}_{id} \times \text{Post}_{td}) + \mu_i + \tau_t + \varepsilon_{itd} \tag{2.4}$$

where i indexes firm, t time, and d the index inclusion event. $Post_{td}$ is a dummy variable equal 1 for the year of the inclusion and the three year afters, and 0 for the four years before. $Treat_{id}$ is a dummy variable equal to 1, if a firm i which is already in the S&P500 experiences the index inclusion of same 4-digit SIC competitor and 0 otherwise in event year d. It's important to note that the firm being added to the index is excluded from the sample and is neither considered a "treatment" nor a "control" for the specific inclusion event. I include firm fixed effect μ_i and year fixed effect τ_t. Standard errors are clustered at the firm level. *** One of the challenges associated with staggered Difference-in-Differences analyses is the potential bias introduced when using already "treated" firms as control groups. This bias can arise if treatment effects vary over time, leading to inaccurate estimates (Baker et al., 2022). To address this concern, I adopt a Stacked DID approach, using firms that have never received treatment as control groups (Cengiz et al., 2019). Panel A of Table 2.4 reports the results. Column (1) to (3) for technological spillover and (4) to (6) for management practice. Column (3) pertains to treated firms in industries with high technological spillover, the coefficient β_3 is statistically significant at the 1% level and positive. This indicates that following the index inclusion of a direct competitor, the markup of the index incumbent firms in the same industry experiences a statistically significant increase of 3%. On the other hand, for firms in industries with low technological spillover (Column 2), the coefficient is not statistically significant, which is in line with hypothesis (1) and preliminary results. Similarly, for treated firms in industries with high management practice (Column 6), the coefficient is statistically significant at the 1% level and positive. The markup of firms in these industries increases by 2.1%. In contrast, for firms in industries with low management practice, the effect is not statistically significant in line with hypothesis (2). In Panel B, I add a set of firm level controls. β_3 remains statistically significant for firms in industries with high management practice and high technological spillover sectors. Figure 2.A.4 illustrates the trend in mean markup before and after the addition of competitors to the S&P500, comparing it with control firms. Initially, I calculated the average markup change between each year t and 3 years before each addition for both the treated and control groups. The figure displays the difference in the average change between the treated and control groups. Post the addition, treated firms exhibit a twofold increase in markup. The relatively stable trend observed before the addition year instills confidence in the construction of the control group.

*** $Post_{it}$ is a dummy that is specific to an inclusion event and therefore does not get absorbed by year fixed effects. In contrast, any given inclusion event assigns all firms to either the treatment or control group. Therefore, the treatment dummy, $Treat_{it}$, is absorbed by firm fixed effects.

In summary, the results of the analysis support the notion that passive common ownership facilitates the internalization of information spillover, leading to an increase in firm markups. Furthermore, the findings suggest that the increase is driven by higher efficiency rather than market power exploitation. In the next section, I will provide additional evidence to further support this point and shed light on the mechanisms through which firms achieve higher markups.

2.4.3. Spillovers in practice

The economic argument stemming from the previous results suggests that common owners play a significant role in disseminating information, which aids firms in internalizing information spillovers. If this hypothesis holds true, we should expect to see a convergence in the corporate strategies of these firms. To explore this hypothesis, I collected data on the names of customers, suppliers, partners, and companies in which a set of firms invested in 2016. Additionally, I obtained a snapshot of job descriptions and job titles from LinkedIn Tech job postings in 2021. Although this dataset captures a single point in time due to its cross-sectional nature, it remains a practical resource, encompassing various dimensions that offers pragmatic insights into the concept of spillover.[†††]

Figure 2.4 illustrates the cosine similarity of a firm's passive investors (QIX) against the cosine similarity of the mentioned variables. Cosine similarity values close to 1 indicate a high degree of similarity, implying that firms share similar investors, customers, partners, and suppliers.[‡‡‡] The positive correlation evident in the scatter plot emphasizes that companies sharing passive investors tend to exhibit parallel attributes, including resemblances in customer bases, supplier networks, partnership affiliations, investments in analogous companies, and even a propensity for recruiting professionals with comparable profiles. These insights provide tangible evidence supporting the notion that passive investors could indeed exert an influence driving firms towards adopting similar strategic approaches in their operations. For further examination, Table 2.2 presents OLS regressions controlling for industry fixed effects. The resulting statistical robustness provides a substantiated basis for the correlations at hand. Importantly, these findings underscore that the observed instances of information sharing and strategic alignment transcend mere coincidental alignments with industry trends. While causality remains unproven, these results add weight to the intriguing role that common ownership plays in fostering information sharing across various corporate entities. Passive investors may indeed assist firms in reallocating their investments toward more profitable and emerging opportunities, evident from the convergence in customer patterns, investment strategies, and hiring practices. This influence might extend to enhancing operational efficiency as well, as it steers firms toward optimizing their supplier choices and encouraging potential partnerships.

[†††] The business relationship and LinkedIn data are sourced from open-source datasets, including platforms like GitHub and Kaggle. For more detailed information about these datasets, please refer to Linkedin dataset and Business relationship dataset

[‡‡‡] Cosine is one the metrics used to computed text similarity

2.5. Efficiency or Market power: A direct test

In this section, I directly investigate whether the information flows facilitated by passive common owners lead to heightened efficiency, thus providing support to the markup results. I analyze two indicators of efficiency: productivity and investment efficiency. Furthermore, to eliminate the possibility that the observed outcomes are attributed to passive common owners promoting market power exploitation, I assess the influence on R&D investment, as well as output levels.

2.5.1. TFP and Investment Efficiency

I calculate Total Factor Productivity (TFP) as firm-level Multifactor Revenue Productivity. In this context, sales represent the output of the production function, while Capital (K) and a bundle of other inputs (M) represent the inputs. To account for intangible capital accurately, I compute Capital (K) following Peters and Taylor (2017a). Due to the unavailability of precise wage bill data in Compustat, I utilize a bundle of inputs (M) instead of labor, as suggested in De Loecker et al. (2020a). In this case, I use the cost of goods sold (COGS) as a proxy for M, which encompasses various expenses related to production goods, including materials, energy, intermediate input, and labor costs. The TFP for each firm i, in sector j, is the residual of the following Cobb-Douglas log regression estimated in each 2–digit SIC industries where the time dummy δ_t serves to detrend the TFP estimates.[§§§]

$$\text{Log Sales}_{i,t} = \beta \text{Log K}_{i,t} + \gamma \text{Log M}_{i,t} + \delta_t + \varepsilon_{i,t} \tag{2.5}$$

In Panel A of Table 2.5, I examine if common owners, by facilitating the internalization of information spillovers, lead to improved productivity. To examine this hypothesis, I estimate the following model separately for firms in industries with high technological spillover and firms in industries with low technological spillover.

$$\text{TFP}_{itd} = \beta_0 + \beta_1 \text{Treat}_{id} + \beta_2 \text{Post}_{td} + \beta_3 (\text{Treat}_{id} \times \text{Post}_{td}) + \mu_i + \tau_t + \varepsilon_{itd} \tag{2.6}$$

Columns (1) to (3) present the results without firm controls, while columns (4) to (6) include firm controls. Column (3) shows that following the inclusion of a competitor in the S&P500, firms in industries with high technological spillover experience a significant 5% increase in productivity and roughly 3% with controls (Column 6). As hypothesized, the coefficient β_3 is not statistically significant for industries with low technological spillover. These findings provide support for the notion that common owners assist firms in internalizing information spillovers, leading to higher productivity and explaining the observed markup results. Panel B reports the results for the management practice sample. Following the inclusion of a competitor

[§§§]The specific details regarding the estimation of the TFP are provided in Appendix 2.A.

in the S&P500, firms in industries with high management practice experience a significant 2% increase in productivity. While there is no effect in industries with bad management practice. Figure 2.A.5 illustrates the trend in mean productivity before and after the addition of competitors to the S&P500, comparing it with control firms. Post the addition, treated firms exhibit a an increase in tfp of 1.5%.

The second proxy for efficiency is investment efficiency measured following the majority of investment literature by regressing investment on investment opportunities (Tobin's Q) measured following Peters and Taylor (2017a), and a set of control variables Z_{it-1} including leverage, cash holdings, size, profitability, size's growth, previous investments as well as industry and year fixed effects (Richardson, 2006).

$$\text{Inv}_{it} = \beta_0 + \beta_1 \text{Tobin Q}_{it-1} + \beta_1 \text{Z}_{it-1} + \upsilon_j + \tau_t + \varepsilon_{it} \tag{2.7}$$

The residuals derived from this regression, denoted as Investment efficiency$_{it}$, capture the extent of divergence from the optimal level investments for each firm i. I then employ the absolute value of these residuals as the dependent variable for the difference-in-differences analysis. This allows me to gauge whether passive common owners enhance investment efficiency by mitigating investment distortion - the overall level of deviations from expected investments.

$$|\text{Investment efficiency}_{itd}| = \beta_0 + \beta_1 \text{Treat}_{id} + \beta_2 \text{Post}_{td} + \beta_3 (\text{Treat}_{id} \times \text{Post}_{td}) + \mu_i + \tau_t + \varepsilon_{itd} \tag{2.8}$$

Column (6) of Panel B suggests that passive common owners by spreading managerial knowledge decrease the deviations from expected investments of 2.2% with respect to the sample mean and therefore increases investment efficiency. This outcome aligns with the findings presented by Antón and Lin (2019), which demonstrate that institutional investors acting as creditors, through the monitoring channel, can effectively enhance firm investment efficiency. My results suggest that also passive common owners, by providing management guidance and facilitating the internalization of spillovers, have the potential to assist firms in reducing over/under investments.

Furthermore, this result provides insights into the level of competition within the market. The negative impact on the residual indicates that the Q theory performs more effectively in cases of high common ownership. This suggests that the Average Q is closer to the true marginal Q in such scenarios. This alignment between Average Q and marginal Q is often associated with markets characterized by perfect competition (Hayashi, 1982a). Hence, the negative impact on the residual not only highlights the positive impact of common ownership on investment efficiency but also points to the presence of more competitive market.

In conclusion, the results strongly indicate that the presence of passive common owners plays a pivotal role in facilitating the internalization of technological spillovers and managerial knowledge within firms. This internalization process, in turn, translates to enhanced efficiency, which can manifest as heightened productivity or improved investment efficiency. These findings provide a potential explanation for the observed outcomes in terms of markups.

2.5.2. R&D and Output

My findings so far suggest that higher markups are driven by improved firm efficiency. However, markups may also be driven by companies exploiting market power and setting high prices. If the market power narrative holds, I would expect common ownership to have a negative impact on output and investment. If common owners reduce the incentive to compete among firms, companies may maximize their profits by reducing output and increasing prices. Moreover, they may lose the incentive to invest in R&D, as they can generate profits by simply increasing prices without the pressure to innovate and improve their products or services (Gutiérrez and Philippon, 2017; Grullon et al., 2019).

To address this concern, I first examine the relationship between common ownership and R&D.

$$\text{R\&D}_{it} = \beta_0 + \beta_1 \text{Treat}_{it} + \beta_2 \text{Post}_{it} + \beta_3 (\text{Treat}_{it} \times \text{Post}_{it}) + \mu_i + \tau_t + \varepsilon_{it} \tag{2.9}$$

where $\text{R\&D}_{it}$ is scaled by $\text{Invested Capital}_{it}$ as in Ayyagari et al. (2023). Panel A of Table 2.7 reports the result for technological spillover and Panel B for management practice. β_3 across the different specification is not significant. The findings suggest that following an increase in common ownership, firms do not significantly reduce their investments. These results are partially consistent with the mixed evidence found in Borochin et al. (2018) on the effect of passive common ownership on innovation. The authors indicate that passive common ownership has no significant impact on innovation in industries with low levels of competition, but it does have a negative impact in industries characterized by high levels of competition.

In Table 2.8, I analyze the effect on firm's output, defined as Sales/Invested Capital (Ayyagari et al., 2023). β_3 is not significant apart for firms in industries with high technological spillover (Panel A Column 6) where is negative and significant at the 5% level. However, once I exclude the firm level controls, the coefficient looses significance, Column (3) of Panel A. To further explore the effect on output, I examine the costs of productions (COGS/Invested Capital) in Table 2.A.4. If firms reduce output following an increase in common ownership, one would expect to observe a decline in the variable component of the production costs. However, the results do not support this hypothesis as there is no significant decline. Taken together, these results suggest that an increase in common ownership does not result in a decrease in output.

Overall, these findings reinforce the idea that common ownership does not lead firms to adopt a strategy of high markups and low output and investment by reducing competitive pressure. Instead, common ownership may contribute to enhance firms' efficiency explaining the positive effect on markups.

2.5.3. Active engagement as a mechanism to diffuse information

Passive investors, despite not actively managing the companies they invest in, can still influence management decisions through various means. One way is through direct participation in decision-making processes, such as exercising proxy votes. Additionally, they can engage in direct discussions, using their "voice" to influence corporate decisions. Regarding the latter, McCahery et al. (2016) point out that a significant proportion of large institutional investors actively engage in discussions with management and private talks with the board [¶¶¶].

Passive investors are strongly motivated to engage due to two main incentives. The first is direct incentives: as the value of a portfolio company increases, it boosts the total assets under management (AUM) of the fund, thereby resulting in higher fees for the fund manager. The second incentive is flow incentives: a surge in a portfolio's value can attract additional capital inflows into the fund (Lewellen and Lewellen, 2021). According to Lewellen and Lewellen (2021), the top five index fund managers (The Big Three, Dimensional, and Schwab) exhibit higher engagement incentives compared to an average institution. For instance, a 1% increase in the value of a typical stockholding raises their annual management fees by $133,000, exceeding an average institution's $84,400 in direct incentives and $129,000 in total incentives as per their sample. These sizable index funds' incentives to drive value creation are akin in magnitude to those of activists, particularly 13D filers. The considerable direct incentives observed among major index asset managers stem from the balance between fees and scale. Despite charging notably lower management fees compared to actively managed funds, their extensive AUM and significant ownership stakes can offset the impact of these lower fees.

BlackRock, among others, recognizing the importance of engagement, has established the BlackRock Investment Stewardship (BIS) division. In a Thomson Reuters article the BIS team is described as "one of the most influential forces in corporate America, given BlackRock's standing as a top shareholder in most big companies. It has been driving change behind the scenes on how companies run themselves ". The primary purpose of these teams is to engage with the management of companies in which BlackRock invests. BIS's local presence enables to understand the specific context in which these companies operate and respond to their unique needs and objectives. The team at BIS further enriches its insights by sharing information about local leadership practices, emerging trends, and policy developments with colleagues globally. This diversity of perspectives augments BIS's efficacy as a trusted client partner and a constructive investor in companies.

To assess whether, behind the scenes, these common owners improved firm efficiency and profit margins by facilitating the exchange of information, I gather data on the engagement of

[¶¶¶] Discussions with top management are used by 63% of institutional investors. Discussions with boards of directors outside of management (45% of institutional investors), proposing specific actions to management (35%), and aggressively questioning management on conference calls (30%)

Thomson Reuters Article

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the BIS team from 2020 to 2022 (Figure 2.A.6 reports an example of the engagement data). I then estimate the following model:

$$\mathrm{Y}_{it} = \alpha + \beta \mathrm{N.\ Engagement}_{it} + \gamma \mathrm{Z}_{it} + \eta_{jt} + \varepsilon_{it} \tag{2.10}$$

Where Y_{it} is either Markup, TFP or Investment efficiency for firm i in year t. N. Engagement is the number of times the BIS team engaged with a firm in a given year. Z_{it} is a set of firm year controls and η_{jt} is industry times year fixed effect.

In Panel A of Table 2.9, the results demonstrate a positive correlation between engagement from the BIS team and markups in industries with high technological spillover (Column 3) and high management practice (Column 6). The positive correlation suggests that the engagement is associated with higher markups, which could be indicative of improved firm efficiency. Panel B, indeed, shows that the engagement is also positive associated with higher total factor productivity in industries with high technological spillover (Column 3) and management practice (Column 6). Similarly, Panel C, shows the negative impact of the engagement on investment distortion, Column (3) and (6). Overall, these results support the notion that engagement by passive common investors can significantly foster the internalization of spillover effects, ultimately contributing to firms' efficiency and profitability. This mechanism can also be seen as a way through which common ownership translates into corporate policies.

2.6. Robustness

In this section, the focus is on three key aspects of the analysis. First, I examine whether the exogenous shock employed in the study has a specific impact on common ownership by QIX investors, rather than affecting other types of institutional investors. Second, I introduce an additional robustness check by utilizing the removal of a competitor from the S&P500 as a negative shock to a firm's common ownership. Lastly, I explore the robustness of the main findings by examining if they hold under different specifications. This includes alternative measures of markups, TFP, technological spillover, and management practice.

2.6.1. Dedidicated and Transient investors

In my analysis, I employ the addition of a stock to the S&P500 as an exogenous shock to the passive common ownership (QIX) of its industry competitors that are already in the index. However, it is important to consider that when a stock is added to an index, it may also attract other types of investors and increase common ownership also by DED and TRA investors. In this scenario, it would be challenging to distinguish the effects among the different types of common ownership. To address possible concerns, I use the following regression:

$$\mathrm{Num.\ connections}_{it} = \beta_0 + \beta_1 \mathrm{S\&P500\ competitor}_{it} + \beta_2 \mathrm{Z}_{it} + \lambda_j + \tau_t + \varepsilon_{it} \tag{2.11}$$

Where Num. connections is the proxy of common ownership for DED and TRA institutional investors for firm i in year t and S&P500 competitor is a dummy variable that takes value 1 if a competitor has been added to the index in a given year and 0 otherwise. Table 2.10 shows that the addition of a competitor to the S&P500 is not correlated with the proxy of DED common ownership (Columns 1 to 2). For TRA common ownership the coefficient is not significant in Column (3), but it turns significant once I include year fixed effect in Column (4). However, transient investors given their short term focus are not normally associated with an improvement in firm productivity or the ability to enhance firm value. Overall, this results suggests that the shock is specific to QIX common ownership and does not extend to other types of institutional investors, supporting the validity of this approach in isolating the impact of QIX common ownership on the outcomes of interest.

2.6.2. Deletions

In this section, I test the robustness of the methodology employed by utilizing the deletion of a competitor from the S&P500 as a negative shock to common ownership. The model estimated is as follows:

$$\mathrm{Y}_{itd} = \beta_0 + \beta_1 \mathrm{Treat}_{id} + \beta_2 \mathrm{Post}_{td} + \beta_3 (\mathrm{Treat}_{id} \times \mathrm{Post}_{td}) + \mu_i + \tau_t + \varepsilon_{itd} \tag{2.12}$$

The outcome variable Y can represent either markup or total factor productivity. Treated is a dummy variable that takes value 1 if a firm is in the S&P500 and a competitor has been deleted from the index, and 0 otherwise. The hypothesis is that a negative shock to common ownership, resulting from the deletion of a competitor, does not generate spillover effects. Consequently, it is expected that firms will not exhibit significant changes in markup and productivity. Table 2.11 presents the results. Columns (1) to (2) show that after the deletion of a competitor from the index, firms in industries with high technological spillover do not experience a significant increase in markups or productivity. Similarly, in sectors with high management practices (Column 3 and 4).

2.6.3. Alternative proxies for technological spillover and management practice

Cohen and Levinthal (1990) introduced the concept of absorptive capacity. They argue that while R&D generates innovation, it also develops the firm's ability to identify, assimilate, and exploit knowledge from the environment - what they call a firm's 'learning' or 'absorptive capacity'. Firms with better absorptive capabilities, therefore, are more likely to benefit from spillover effects. In this spirit, I proxy technological spillover and management practice with a firm's absorptive capacity. Respectively, I use the variables knowledge and organizational capital from Peters and Taylor (2017a).

Knowledge capital represents the firm's accumulated knowledge and expertise, which can be attributed to its past investments in research and development activities. Firms with higher knowledge capital are assumed to be in a better position to internalize technological spillovers. This means that they are more capable of incorporating external knowledge and applying it to their own operations, resulting in increased efficiency and productivity. On the other hand, organizational capital captures the firm's ability to effectively organize and utilize its resources. It encompasses various factors such as human capital, organizational routines, and processes. Firms with higher organizational capital are considered to have superior managerial capabilities and are better equipped to internalize managerial knowledge. This implies that they can effectively implement best practices, optimize their operations, and drive improvements in their overall performance.

Table 2.12 reports the results of the baseline Difference in Differences model where treated firms are divided into two groups based on their knowledge capital and organizational capital, using the median value as the threshold.

Panel A indicates that the inclusion of a competitor in the index leads to a 3.3% increase in markups for firms in industries with high technological spillover (Column 3). Similarly, firms with high organizational capital experience a 2.1% increase in markups following the inclusion (Column 6). Panel B shows that the productivity results are consistent with those for markups. Firms with high technological spillover experience a 1.8% increase in productivity after the inclusion of a competitor (Column 3). Similarly, firms with high organizational capital exhibit a 1.2% increase in productivity (Column 6). Overall, these results suggest that the initial findings regarding the impact of common ownership on firms' outcomes are robust, as they hold across different proxies for a firm's ability to internalize spillover effects (technological spillover and organizational capital).

2.6.4. Alternative markup and TFP definitions

The choice of an appropriate measure of markup has been a subject of debate in the literature. In the current analysis, I used the measure proposed by De Loecker et al. (2020a), which is derived from the production function approach. However, following the suggestions of Ayyagari et al. (2023), I propose an alternative direct measure of markups that avoid some of the econometric and optimization challenges associated with the production function approach.

Traina (2018) highlight that using COGS as a measure of variable costs does not account for the fact that while COGS is declining for US firms other expenses such as Selling, General, and Administrative Expenses are increasing. Therefore use Operating expenses (OPEX) as a variable costs should be more appropriate. However, Ayyagari et al. (2023) argue that certain expenses, such as R&D and a portion of SG&A, should be considered capital expenses that contribute to building the firm's capital stock rather than operating expenses. To address this concern, they propose a corrected measure of operating expenses (OPEX*) by subtracting R&D

and RDIP expenses, as well as 0.3 times the SG&A expenses (OPEX* = OPEX - R&D - RDIP - 0.3xSG&A). Markups is then defined as SALES/OPEX*.

Panel A of Table 2.13 presents the results using the alternative measure of markups. The coefficients are significant at the 5% level for firms in industries with high technological spillover. The economic magnitude of the coefficient is 2.6%, indicating a substantial increase in markups for these firms following the inclusion of a competitor in the index. In the case of firms in sectors with high management practice, although the coefficient loses statistical significance, it remains significant at the 10% level. This suggests that the inclusion of a competitor still has a positive impact on markups for firms with high management practice.

In the analysis, total factor productivity (TFP) is computed using the Olley and Pakes correction, which helps mitigate concerns related to simultaneity biases, Appendix 2.A. Panel B shows the results using standard OLS TFP estimation without the Olley and Pakes correction. The inclusion of a competitor in the index leads to improvements in firms' productivity by 1.5% and 1.2% in industries with high technological spillover and high management practice, respectively. These coefficients remain significant at the 1% and 5% levels, indicating a consistent positive association between the shock and increased productivity for firms operating in these industries.

2.7. Conclusion

Common ownership holds the potential to either facilitate anti-competitive behavior through the support of market power exploitation or to assist firms in internalizing spillovers by promoting the dissemination of information, thereby enhancing their efficiency. Recent empirical findings show that the latter phenomenon holds true, particularly for active common owners like venture capital in private market. This paper posits that passive common owners in public market also exhibit comparable behavior. Through their active engagement in the companies they invest in, passive common owners contribute to the exchange of information among firms. This proactive participation translates into enhanced firm efficiency and, consequently, results in higher markups.

By using the addition of a competitor to the S&P 500 as exogenous shocks, I find evidence that passive common owners positively affect firm markups. This effect is particularly pronounced in industries with high technological spillover and good management practices, where the incorporation of information is more effective. The positive impact on markups results from improved firm efficiency, measured by variables like total factor productivity and investment efficiency. Importantly, this effect is not driven by firm market power exploitation, as there is no observed drop in R&D investment or output levels. Besides, I underscore the significance of active engagement by passive common owners in the information dissemination process. This active engagement serves as a key mechanism through which the influence of passive common ownership shifts into firm policies.

The paper holds significant policy implications. While it highlights a positive aspect of common ownership, it also raises certain concerns. Passive investors are likely to engage more with large companies, as these firms are key components of the index that these investors replicate. This prompts the questions: Do large firms under the ownership of these index investors benefit more from this information dissemination? Could this lead to resource misallocation or a competitive advantage for these larger firms? Does it contribute to the emergence of star firms within the economy and to the rising productivity gap between leaders and laggards? Policy-makers must carefully weigh the trade-off between fostering the growth and innovation potential of large firms, potentially facilitated by common ownership, and addressing the potential increase in market concentration that could result from it. Striking the right balance is essential to uphold a competitive and dynamic market landscape. Additional research is warranted to comprehensively grasp the welfare implications of common ownership and its effects on market outcomes, as well as explore other potential mechanisms of information transmission.

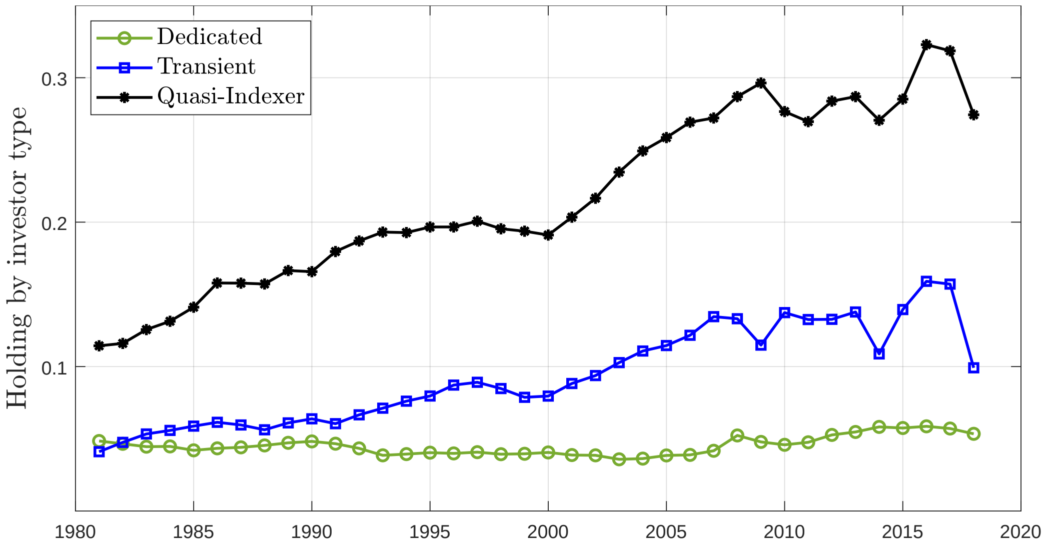

Fig. 2.1 **Equity holding by type of institutional investor:** This figure shows the yearly percentage equity holding for each type of investor. Following Bushee (1998) and Bushee (2001), I disentangle institutional investors into three categories: "Dedicated", "Quasi-indexers" and "Transient".

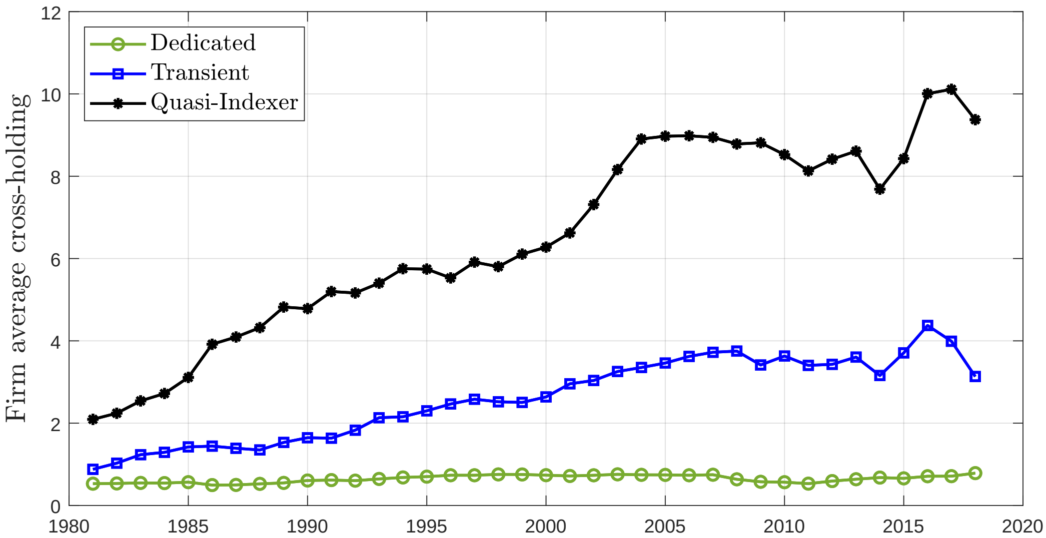

Fig. 2.2 **Common ownership by type of institutional investor:** This figure plots the yearly common ownership for each type of investor. Investor types, following Bushee (1998) and Bushee (2001), are divided in three categories: "Dedicated", "Transient" and "Quasi-indexers". Common ownership is the number of unique institutions that cross-held the firms, *NumCross* in He and Huang (2017).

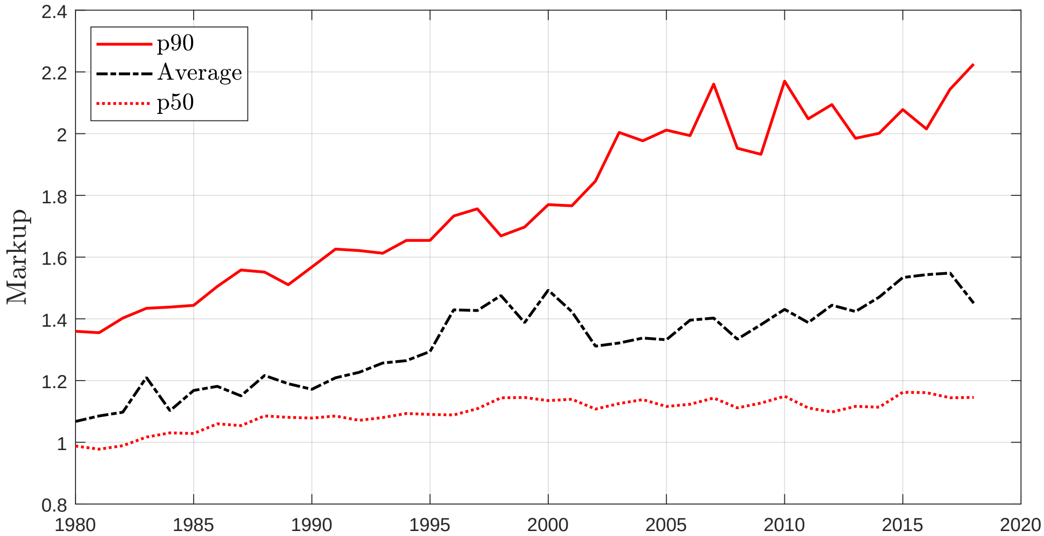

Fig. 2.3 **Markup percentiles over time:** This figure illustrates the average, p50 and p90 time series of markups from 1980 to 2018. The percentiles are revenue weighted. Markups are computed following De Loecker et al. (2020a).

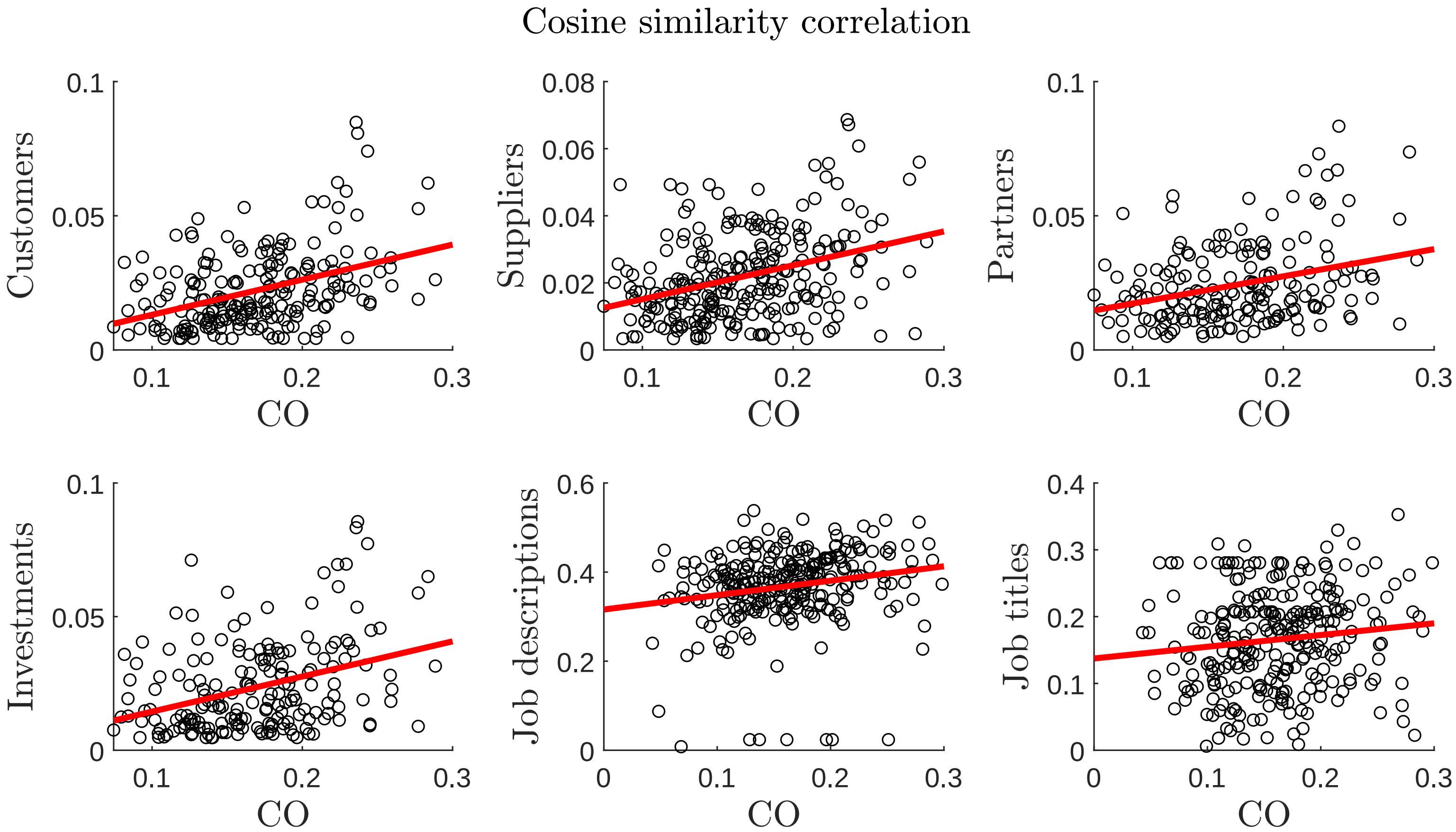

Fig. 2.4 **Cosine similarities scatter plot:** This figure illustrates the correlation between passive investors (QIX) cosine similarity and the cosine similarities of various aspects, including customers, suppliers, partners, investments, job descriptions, and job titles. Cosine similarities are computed among peers belonging to the same 12 Fama-French industry group. The data for business relationships date back to 2016, while the job posting data is from 2021. For additional details, please consult Linkedin dataset and Business relationship dataset

Table 2.1 **Summary statistics**
This table presents descriptive statistics of the main variables for the technological spillover (Panel A) and management practice (Panel B) sample.

Panel A: Technological spillover

	Mean	p25	p50	p75	sd	N
Markup (De Loecker)	1.58	1.11	1.3	1.67	0.96	97350
Markup (Opex)	1.96	1.31	1.56	2.17	1.17	97350
Tfp	1.82	1.31	1.54	1.97	0.87	97350
Investment efficiency	0.27	0.18	0.22	0.30	0.15	90933
R&D	1.36	0.81	1.19	1.7	0.82	97350
Output	0.04	0	0	0.06	0.06	97350
Size	5.45	4.1	5.22	6.62	1.78	97350
Market to Book	2.54	1.08	1.8	3.07	2.28	97350
Roa	-0.01	-0.03	0.03	0.07	0.14	97350
PP&E/Assets	0.31	0.14	0.25	0.43	0.22	97350
Totatl debt/Assets	0.23	0.06	0.21	0.36	0.19	97350
Capex/Assets	0.07	0.02	0.05	0.09	0.06	97350
% Inst. Ownership	0.45	0.19	0.42	0.7	0.29	70508
QIX Num. connections	22.95	3	8.5	25	34.89	69043
BIS Engagement	.27	0	0	0	.75	6889
K int Know (MM)	200.99	0	2.61	41.9	1658.68	97350
K int Org (MM)	394.5	16.12	46.71	166.99	2292.68	97350

Panel B: Management practice

	Mean	p25	p50	p75	sd	N
Markup (De Loecker)	1.65	1.13	1.34	1.74	1.14	13175
Markup (Opex)	2.07	1.34	1.64	2.32	1.31	13175
Tfp	2.19	1.27	1.46	1.95	1.72	13175
Investment efficiency	0.24	0.17	0.21	0.27	0.12	12855
R&D	1.17	0.74	1.05	1.44	0.67	13175
Output	0.05	0	0.03	0.08	0.06	13175
Size	6.27	4.87	6.23	7.62	1.85	13175
Market to Book	2.8	1.25	2.04	3.49	2.36	13175
Roa	-0.01	-0.04	0.04	0.08	0.16	13175
PP&E/Assets	0.22	0.1	0.17	0.29	0.16	13175
Totatl debt/Assets	0.2	0.03	0.17	0.31	0.18	13175
Capex/Assets	0.04	0.02	0.03	0.05	0.04	13175
% Inst. Ownership	0.67	0.5	0.76	0.9	0.27	10716
QIX Num. connections	19.7	3	7.75	19	28.47	10711
BIS Engagement	.31	0	0	0	0.8	3513
K int Know (MM)	642.36	3.42	47.7	219.9	3703.45	13175
K int Org (MM)	658.75	36.88	108.9	399.76	2273.67	13175

Table 2.2 Cosine Similarity OLS regressions

This table presents estimates from OLS regressions of passive investors (QIX) cosine similarity on the cosine similarities of various aspects, including customers, suppliers, partners, investments, job descriptions, and job titles. Cosine similarities are computed among peers belonging to the same 12 Fama-French industry group. The data for business relationships date back to 2016, while the job posting data is from 2021. For additional details, please consult Linkedin dataset and Business relationship dataset. Each regression includes industry (12 Fama-French industry) fixed effect. Robust Standard errors are reported under each estimate in parentheses. Estimates followed by $***$, $**$, and $*$ have p-values lower than 0.01, 0.05, and 0.1.

	Common ownership	Industry fixed effect	R^2	N
Customer	0.147***	Yes	0.405	211
	(0.022)			
Suppliers	0.122***	Yes	0.212	259
	(0.020)			
Partners	0.12***	Yes	0.293	181
	(0.026)			
Investments	0.147***	Yes	0.334	191
	(0.28)			
Job description	0.371***	Yes	0.115	271
	(0.112)			
Job title	0.189**	Yes	0.034	272
	(0.095)			

Table 2.3 Markup and passive common ownership
This table presents estimates from panel regressions of the one year-ahead price-marginal markup in logarithmic form (De Loecker et al., 2020a), on the unique number of connections via QIX common owners. Additional control variables are Size, Market to Book, Roa, % of Institutional ownership and PP&E, Total debt and Capex scaled by Total Assets. The table is divided into two sets of columns: (1) to (3) represent estimates from the technological spillover sample, and (4) to (6) represent estimates from the management practice sample. Each regression includes industry fixed effect (4 digit SIC) and year fixed effect. Standard errors clustered at firm level are reported under each estimate in parentheses. Estimates followed by $***$, $**$, and $*$ have p-values lower than 0.01, 0.05, and 0.1.

Dependent variable	Log markup$_{t+1}$					
	Technological spillover			Management practice		
	All	Low	High	All	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
N. connections	0.001**	0.000	0.001***	0.002**	0.002	0.003**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Size	0.001	-0.000	0.000	0.010*	0.019**	-0.002
	(0.003)	(0.005)	(0.005)	(0.006)	(0.008)	(0.009)
Market to book	0.027***	0.024***	0.032***	0.036***	0.034***	0.037***
	(0.002)	(0.002)	(0.002)	(0.004)	(0.006)	(0.005)
Roa	0.425***	0.299***	0.527***	0.433***	0.703***	0.249***
	(0.029)	(0.042)	(0.040)	(0.068)	(0.129)	(0.066)
PP&E/Assets	-0.083***	-0.036	-0.121***	-0.408***	-0.354***	-0.467***
	(0.030)	(0.038)	(0.045)	(0.067)	(0.086)	(0.107)
Total debt/Assets	-0.115***	-0.101***	-0.137***	-0.083*	-0.058	-0.093
	(0.019)	(0.024)	(0.031)	(0.043)	(0.063)	(0.060)
Capex/Assets	0.259***	0.209**	0.306***	0.328	-0.097	0.757**
	(0.066)	(0.086)	(0.098)	(0.216)	(0.253)	(0.352)
% Inst. Ownership	0.094***	0.062**	0.138***	0.091***	0.040	0.154***
	(0.019)	(0.026)	(0.028)	(0.033)	(0.048)	(0.045)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	59,809	32,123	27,686	11,941	5,971	5,970
R^2	0.442	0.503	0.362	0.532	0.563	0.494

Table 2.4 Markup and passive common ownership - Difference in differences

This table presents the difference in differences estimates using S&P500 inclusions of competitors. The dependent variable is the price-marginal markup in logarithmic form (De Loecker et al., 2020a). Firms that are already in the S&P500 index and are in an industry that experiences an addition of a competitor firm to the S&P500 in a given year are the treatment group, and all other firms in different industries that did not experience an inclusion in the index are the control firms. The Post dummy takes value of 1 for the event year and for the three years after the inclusion, and takes value of 0 for the four years before. Panel B includes additional control variables: Size, Market to Book, Roa, % of Institutional ownership and PP&E, Total debt and Capex scaled by Total Assets. The table are divided into two sets of columns: (1) to (3) represent estimates from the technological spillover sample, and (4) to (6) represent estimates from the management practice sample. Each regression includes firm fixed effect and year fixed effect. Standard errors clustered at firm level are reported under each estimate in parentheses. Estimates followed by $***, **$, and $*$ have p-values lower than 0.01, 0.05, and 0.1.

Panel A: Difference in differences

Dependent variable	Log markup					
	Technological spillover			Management practice		
	All	Low	High	All	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
Post x Treated	0.018***	0.004	0.030***	0.027**	0.032	0.021***
	(0.006)	(0.008)	(0.008)	(0.011)	(0.020)	(0.008)
Post	-0.010***	-0.006***	-0.010***	-0.003**	-0.003*	-0.003*
	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.001)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,815	14,492	14,313	5,684	5,137	5,080
R^2	0.916	0.910	0.945	0.973	0.975	0.977

(Table continues)

Table 2.4 *-continued*

Panel B: Difference in differences with controls

Dependent variable	Log markup					
	Technological spillover			Management practice		
	All	Low	High	All	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
Post x Treated	0.009	0.001	0.018***	0.012**	0.010	0.013**
	(0.006)	(0.008)	(0.007)	(0.006)	(0.009)	(0.006)
Post	-0.006**	-0.002	-0.006***	-0.002*	-0.002	-0.002*
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Size	0.001	0.005	0.000	0.020	0.013	0.022
	(0.020)	(0.022)	(0.016)	(0.021)	(0.020)	(0.020)
Market to book	0.002	0.001	0.007***	0.004	0.004	0.004
	(0.004)	(0.005)	(0.002)	(0.003)	(0.003)	(0.003)
Roa	1.022***	1.187***	0.481***	0.327***	0.297**	0.311***
	(0.220)	(0.282)	(0.063)	(0.103)	(0.116)	(0.101)
PP&E/Assets	0.249*	0.360**	-0.024	-0.037	-0.023	-0.063
	(0.145)	(0.167)	(0.084)	(0.177)	(0.195)	(0.199)
Total debt/Assets	-0.012	0.047	-0.007	-0.007	-0.012	-0.002
	(0.071)	(0.081)	(0.038)	(0.059)	(0.065)	(0.056)
Capex/Assets	-0.196	-0.116	-0.178	0.094	0.163	0.275
	(0.205)	(0.225)	(0.138)	(0.203)	(0.249)	(0.202)
% Inst. Ownership	-0.176*	-0.060	-0.236***	-0.119	-0.162*	-0.045
	(0.091)	(0.094)	(0.068)	(0.081)	(0.087)	(0.068)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,809	11,052	10,864	4,942	4,442	4,440
R^2	0.932	0.923	0.960	0.980	0.982	0.977

Table 2.5 **Total factor productivity**

This table presents the difference in differences estimates using S&P500 inclusions of competitors. The dependent variable is the total factor productivity in logarithmic form computed as the residual of standard Cobb Douglas regression (Appendix 2.A). Firms that are already in the S&P500 index and are in an industry that experiences an addition of a competitor firm to the S&P500 in a given year are the treatment group, and all other firms in different industries that did not experience an inclusion in the index are the control firms. The Post dummy takes value of 1 for the event year and for the three years after the inclusion, and takes value of 0 for the four years before. Panel A reports the results for technological spillover sample and panel B for the management practice sample. Firm controls include: Size, Market to Book, Roa, % of Institutional ownership and PP&E, Total debt and Capex scaled by Total Assets. Each regression includes firm fixed effect and year fixed effect. Standard errors clustered at firm level are reported under each estimate in parentheses. Estimates followed by $***$, $**$, and $*$ have p-values lower than 0.01, 0.05, and 0.1.

Panel A: Technological spillover

Dependent variable	TFP					
	Technological spillover					
	All	Low	High	All	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
Post x Treated	0.021***	-0.002	0.046***	0.014*	0.003	0.028***
	(0.008)	(0.009)	(0.010)	(0.007)	(0.009)	(0.010)
Post	-0.014***	-0.003	-0.017***	-0.008**	-0.000	-0.011***
	(0.004)	(0.003)	(0.005)	(0.004)	(0.002)	(0.004)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	No	No	No	Yes	Yes	Yes
Observations	15,357	13,124	12,842	12,145	10,429	10,135
R^2	0.948	0.946	0.959	0.958	0.955	0.969

Panel B: Management practice

Dependent variable	TFP					
	Management practice					
	All	Low	High	All	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
Post x Treated	0.018***	0.013*	0.024***	0.015***	0.011	0.019**
	(0.006)	(0.008)	(0.008)	(0.005)	(0.007)	(0.007)
Post	-0.002	-0.000	-0.003*	-0.002	-0.000	-0.002*
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	No	No	No	Yes	Yes	Yes
Observations	6,235	5,248	4,988	5,672	4,777	4,534
R^2	0.978	0.966	0.988	0.981	0.970	0.990

Table 2.6 Investment efficiency

This table presents the difference in differences estimates using S&P500 inclusions of competitors. The dependent variable is investment efficiency computed following Richardson (2006). Firms that are already in the S&P500 index and are in an industry that experiences an addition of a competitor firm to the S&P500 in a given year are the treatment group, and all other firms in different industries that did not experience an inclusion in the index are the control firms. The Post dummy takes value of 1 for the event year and for the three years after the inclusion, and takes value of 0 for the four years before. Panel A reports the results for technological spillover sample and panel B for the management practice sample. Firm controls include: Size, Market to Book, Roa, % of Institutional ownership and PP&E, Total debt and Capex scaled by Total Assets. Each regression includes firm fixed effect and year fixed effect. Standard errors clustered at firm level are reported under each estimate in parentheses. Estimates followed by $***$, $**$, and $*$ have p-values lower than 0.01, 0.05, and 0.1.

Panel A: Technological spillover

Dependent variable	Investment efficiency					
	Technological spillover					
	All (1)	Low (2)	High (3)	All (4)	Low (5)	High (6)
Post x Treated	-0.001	-0.004	0.002	-0.003	-0.003	-0.002
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
Post	-0.004***	-0.004***	-0.004***	-0.002***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	No	No	No	Yes	Yes	Yes
Observations	15,114	12,899	12,655	12,108	10,396	10,109
R^2	0.721	0.720	0.729	0.783	0.791	0.802

Panel B: Management practice

Dependent variable	Investment efficiency					
	Management practice					
	All (1)	Low (2)	High (3)	All (4)	Low (5)	High (6)
Post x Treated	-0.003	-0.001	-0.005*	-0.003**	-0.001	-0.006**
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Post	-0.001	-0.001	-0.001	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	No	No	No	Yes	Yes	Yes
Observations	6,336	5,344	5,074	5,753	4,852	4,609
R^2	0.820	0.816	0.812	0.850	0.849	0.852

Table 2.7 R&D

This table presents the difference in differences estimates using S&P500 inclusions of competitors. The dependent variable is R&D scaled by invested capital as in Ayyagari et al. (2023). Firms that are already in the S&P500 index and are in an industry that experiences an addition of a competitor firm to the S&P500 in a given year are the treatment group, and all other firms in different industries that did not experience an inclusion in the index are the control firms. The Post dummy takes value of 1 for the event year and for the three years after the inclusion, and takes value of 0 for the four years before. Panel A reports the results for technological spillover sample and panel B for the management practice sample. Firm controls include: Size, Market to Book, Roa, % of Institutional ownership and PP&E, Total debt and Capex scaled by Total Assets. Each regression includes firm fixed effect and year fixed effect. Standard errors clustered at firm level are reported under each estimate in parentheses. Estimates followed by $***$, $**$, and $*$ have p-values lower than 0.01, 0.05, and 0.1.

Panel A: Technological spillover

Dependent variable	R&D					
	Technological spillover					
	All (1)	Low (2)	High (3)	All (4)	Low (5)	High (6)
Post x Treated	0.000	-0.001*	0.001	0.000	-0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Post	-0.001***	-0.000**	-0.001***	-0.000**	-0.000*	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	No	No	No	Yes	Yes	Yes
Observations	15,340	13,105	12,825	12,133	10,414	10,123
R^2	0.923	0.925	0.915	0.929	0.931	0.917

Panel B: Management practice

Dependent variable	R&D					
	Management practice					
	All (1)	Low (2)	High (3)	All (4)	Low (5)	High (6)
Post x Treated	-0.001**	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Post	-0.000	-0.000	0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	No	No	No	Yes	Yes	Yes
Observations	6,238	5.251	4,991	5,672	4,777	4,534
R^2	0.957	0.960	0.951	0.959	0.961	0.953

Table 2.8 **Output**

This table presents the difference in differences estimates using S&P500 inclusions of competitors. The dependent variable is Output computed as Sales over invested capital as in Ayyagari et al. (2023). Firms that are already in the S&P500 index and are in an industry that experiences an addition of a competitor firm to the S&P500 in a given year are the treatment group, and all other firms in different industries that did not experience an inclusion in the index are the control firms. The Post dummy takes value of 1 for the event year and for the three years after the inclusion, and takes value of 0 for the four years before. Panel A reports the results for technological spillover sample and panel B for the management practice sample. Firm controls include: Size, Market to Book, Roa, % of Institutional ownership and PP&E, Total debt and Capex scaled by Total Assets. Each regression includes firm fixed effect and year fixed effect. Standard errors clustered at firm level are reported under each estimate in parentheses. Estimates followed by $***$, $**$, and $*$ have p-values lower than 0.01, 0.05, and 0.1.

Panel A: Technological spillover

Dependent variable	Output					
	Technological spillover					
	All (1)	Low (2)	High (3)	All (4)	Low (5)	High (6)
Post x Treated	-0.012 (0.011)	-0.015 (0.016)	-0.008 (0.012)	-0.012 (0.011)	-0.000 (0.015)	-0.025** (0.012)
Post	-0.005 (0.005)	-0.009* (0.005)	-0.009* (0.005)	-0.000 (0.005)	-0.003 (0.005)	-0.003 (0.005)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	No	No	No	Yes	Yes	Yes
Observations	15,340	13,105	12,825	12,133	10,414	10,123
R^2	0.857	0.851	0.865	0.884	0.883	0.889

Panel B: Management practice

Dependent variable	Output					
	Management practice					
	All (1)	Low (2)	High (3)	All (4)	Low (5)	High (6)
Post x Treated	0.022 (0.014)	0.025 (0.020)	0.016 (0.011)	0.019 (0.013)	0.027 (0.019)	0.013 (0.011)
Post	-0.003 (0.006)	-0.001 (0.007)	-0.006 (0.006)	-0.000 (0.006)	0.001 (0.006)	-0.000 (0.005)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	No	No	No	Yes	Yes	Yes
Observations	6,238	5,251	4,991	5,672	4,777	4,534
R^2	0.916	0.907	0.934	0.938	0.932	0.949

Table 2.9 **Engagement outcomes**

This table presents estimates from panel regressions of markup (Panel A), total factor productivity in logarithmic form (Panel B) and investment effieciciency (Panel C) on the number of engagement from the BlackRock Investment Stewardship (BIS) team also in logarithmic form. Additional control variables are Size, Market to Book, Roa and PP&E, Total debt and Capex scaled by Total Assets and if a firm is member of the S&P500. The table is divided into two sets of columns: (1) to (3) represent estimates from the technological spillover sample, and (4) to (6) represent estimates from the management practice sample. Each regression includes industry (4 digit SIC) time year fixed effect. Standard errors clustered at firm level are reported under each estimate in parentheses. Estimates followed by $***$, $**$, and $*$ have p-values lower than 0.01, 0.05, and 0.1.

Panel A: Markup

Dependent variable	Log Markup					
	Technological spillover			Management practice		
	All	Low	High	All	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
N. engagement	0.040	-0.006	0.108*	0.087*	0.088	0.071**
	(0.031)	(0.025)	(0.060)	(0.048)	(0.080)	(0.035)
Size	0.023***	0.000	0.047***	0.034**	0.074***	0.010
	(0.009)	(0.008)	(0.016)	(0.014)	(0.024)	(0.015)
Market to book	0.006***	0.005***	0.005	0.006*	0.004	0.007***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.005)	(0.002)
Roa	1.474***	0.774***	1.973***	1.844***	2.137***	1.151***
	(0.138)	(0.096)	(0.226)	(0.220)	(0.292)	(0.275)
PP&E/Assets	-0.237**	-0.153*	-0.237	-0.340	-0.314	-0.167
	(0.104)	(0.081)	(0.225)	(0.207)	(0.295)	(0.274)
Total debt/Assets	0.368***	0.094*	0.732***	0.595***	0.994***	0.079
	(0.083)	(0.054)	(0.169)	(0.153)	(0.229)	(0.163)
Capex/Assets	-0.095	-0.098	-0.451	0.485	1.025	0.101
	(0.425)	(0.374)	(0.870)	(0.902)	(1.412)	(1.147)
S&P500 member	-0.020	0.074*	-0.135*	-0.069	-0.043	-0.031
	(0.040)	(0.040)	(0.071)	(0.058)	(0.106)	(0.047)
Industry x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,827	3,230	2,597	3,150	1,580	1,570
R^2	0.315	0.440	0.298	0.264	0.264	0.234

(Table continues)

Table 2.9 -*continued*

Panel B: TFP

Dependent variable	TFP					
	Technological spillover			Management practice		
	All	Low	High	All	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
N. engagements	0.046	-0.021	0.142**	0.100**	0.140*	0.065**
	(0.029)	(0.025)	(0.064)	(0.043)	(0.084)	(0.028)
Size	0.083***	0.070***	0.093***	0.047***	0.052**	0.039***
	(0.007)	(0.007)	(0.014)	(0.011)	(0.022)	(0.009)
Market to book	0.001	0.001	0.001	0.001	0.001	0.002*
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)
Roa	0.153***	0.197***	0.153	0.242**	0.208	0.438***
	(0.058)	(0.059)	(0.101)	(0.115)	(0.129)	(0.110)
PP&E/Assets	-0.239**	-0.557***	0.275	-0.186	-0.176	-0.260**
	(0.110)	(0.112)	(0.211)	(0.174)	(0.291)	(0.115)
Total debt/Assets	0.086***	0.017	0.187***	0.199**	0.331***	0.123**
	(0.033)	(0.028)	(0.072)	(0.084)	(0.101)	(0.050)
Capex/Assets	0.055	0.279	-0.569	0.870	2.434	-0.295
	(0.428)	(0.340)	(1.021)	(0.804)	(1.542)	(0.542)
S&P500 member	0.019	0.077**	-0.067	0.075	0.108	0.044
	(0.037)	(0.033)	(0.084)	(0.054)	(0.138)	(0.035)
Industry x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,058	4,258	2,800	3,836	1,693	2,143
R^2	0.706	0.853	0.583	0.622	0.351	0.843

(Table continues)

Table 2.9 *-continued*

Panel C: Investment efficiency

Dependent variable	Investment efficiency					
	Technological spillover			Management practice		
	All	Low	High	All	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
N. engagements	-0.002	0.006	-0.017**	-0.012*	-0.009	-0.015*
	(0.006)	(0.008)	(0.008)	(0.006)	(0.009)	(0.009)
Size	-0.017***	-0.014***	-0.019***	-0.018***	-0.023***	-0.014***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Market to book	0.001**	0.001***	0.000	0.000	-0.000	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Roa	-0.000	-0.007	0.002	-0.003	0.002	-0.007
	(0.005)	(0.009)	(0.005)	(0.005)	(0.005)	(0.009)
PP&E/Assets	-0.212***	-0.251***	-0.191***	-0.209***	-0.138**	-0.311***
	(0.022)	(0.033)	(0.028)	(0.044)	(0.056)	(0.058)
Total debt/Assets	-0.004	-0.002	-0.006	-0.009*	-0.009	-0.009
	(0.004)	(0.006)	(0.006)	(0.005)	(0.007)	(0.009)
Capex/Assets	0.752***	1.127***	0.436***	0.908***	0.493**	1.352***
	(0.110)	(0.172)	(0.130)	(0.201)	(0.205)	(0.322)
S&P500 member	0.030***	0.022***	0.037***	0.039***	0.039***	0.029***
	(0.006)	(0.008)	(0.010)	(0.009)	(0.012)	(0.010)
Industry x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,536	3,944	3,592	4,176	2,077	2,099
R^2	0.137	0.158	0.132	0.107	0.103	0.119

Table 2.10 Shock and investor type

This table presents estimates from panel regressions of number of connections in logarithmic form via DED common owners (Column 1 to 2) and via TRA common owners (Column 3 to 4) on a dummy variable that takes value 1 if a competitor is added to the S&P500 and 0 otherwise. Additional control variables are Size, Market to Book, Roa, % of Institutional ownership and PP&E, Total debt and Capex scaled by Total Assets. Each regression includes firm fixed effect and year fixed effect. Standard errors clustered at firm level are reported under each estimate in parentheses. Estimates followed by $***$, $**$, and $*$ have p-values lower than 0.01, 0.05, and 0.1.

Dependent variable	N. connections			
	DED		TRA	
	(1)	(2)	(3)	(4)
SP&500 Competitor	0.017	0.032	0.026	0.059***
	(0.025)	(0.022)	(0.019)	(0.017)
Firm Control	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
Observation	7,102	7,102	10,696	10,696
R^2	0.032	0.189	0.177	0.376

Table 2.11 **Difference in Differences with deletions**

This table presents the difference in differences estimates using S&P500 deletions of competitors. The dependent variables are the price-marginal markup (De Loecker et al., 2020a) and the total factor productivity in logarithmic form. Firms that are already in the S&P500 index and are in an industry that experiences a deletion of a competitor firm from the S&P500 in a given year are the treatment group, and all other firms in different industries that did not experience a deletion from the index are the control firms. The Post dummy takes value of 1 for the event year and for the three years after the inclusion, and takes value of 0 for the four years before. Additional control variables are Size, Market to Book, Roa, % of Institutional ownership and PP&E, Total debt and Capex scaled by Total Assets. The tables are divided into two sets of columns: (1) to (2) represent estimates from the high technological spillover sample, and (3) to (4) represent estimates from the high management practice sample. Each regression includes firm fixed effect and year fixed effect. Standard errors clustered at firm level are reported under each estimate in parentheses. Estimates followed by $***$, $**$, and $*$ have p-values lower than 0.01, 0.05, and 0.1.

	High technological spillover		High management practice	
	Markup	TFP	Markup	TFP
	(1)	(2)	(3)	(4)
Treated x Post	0.009	0.010	0.002	-0.010
	(0.008)	(0.009)	(0.008)	(0.006)
Post	-0.003	-0.012***	-0.002	-0.005***
	(0.002)	(0.003)	(0.001)	(0.002)
Size	-0.003	-0.057	0.058	-0.014
	(0.028)	(0.047)	(0.035)	(0.028)
Market to book	0.001	0.015**	0.004	0.006
	(0.004)	(0.006)	(0.005)	(0.005)
Roa	0.479***	0.516***	0.507***	0.490***
	(0.103)	(0.169)	(0.158)	(0.157)
PP&E/Assets	-0.124	-0.483***	0.104	-0.019
	(0.135)	(0.181)	(0.226)	(0.256)
Total debt/Assets	-0.125	-0.150*	-0.031	-0.272***
	(0.080)	(0.082)	(0.080)	(0.084)
Capex/Assets	-0.272	0.054	-0.276	-0.343
	(0.246)	(0.483)	(0.341)	(0.362)
% Inst. Ownership	-0.349**	0.132	-0.133	0.031
	(0.173)	(0.196)	(0.167)	(0.165)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	4,924	5,160	2,948	2,736
R^2	0.958	0.970	0.978	0.990

Table 2.12 **Knowledge and Organizational capital**

This table presents the difference in differences estimates using S&P500 inclusions of competitors. Knowledge capital and organizational capital (Peters and Taylor, 2017a) are used as proxy for technological spillover and management practice. The dependent variable is the price-marginal markup in logarithmic form (De Loecker et al., 2020a) in Panel A and the total factor productivity in Panel B also in logarithmic form. Firms that are already in the S&P500 index and are in an industry that experiences an addition of a competitor firm to the S&P500 in a given year are the treatment group, and all other firms in different industries that did not experience an inclusion in the index are the control firms. The Post dummy takes value of 1 for the event year and for the three years after the inclusion, and takes value of 0 for the four years before. Panel B includes additional control variables: Size, Market to Book, Roa, % of Institutional ownership and PP&E, Total debt and Capex scaled by Total Assets. The tables are divided into two sets of columns: (2) to (3) represent estimates using knowldge capital, and (4) to (5) represent estimates from the organizational capital sample. Each regression includes firm fixed effect and year fixed effect. Standard errors clustered at firm level are reported under each estimate in parentheses. Estimates followed by $***$, $**$, and $*$ have p-values lower than 0.01, 0.05, and 0.1.

Panel A: Markup

Dependent variable	Log markup				
		Knowledge Capital		Organizational Capital	
	All	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)
Post x Treated	0.014*	-0.004	0.033***	-0.003	0.021***
	(0.007)	(0.008)	(0.009)	(0.009)	(0.008)
Post	-0.008**	-0.001	-0.009**	-0.002	-0.007**
	(0.004)	(0.002)	(0.004)	(0.002)	(0.003)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes
Observations	12,145	10,207	10,350	10,225	10,332
R^2	0.958	0.961	0.965	0.965	0.965

Panel B: TFP

Dependent variable	TFP				
		Knowledge Capital		Organizational Capital	
	All	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)
Post x Treated	0.008	-0.006	0.018***	-0.002	0.012**
	(0.006)	(0.008)	(0.006)	(0.009)	(0.005)
Post	-0.005**	-0.001	-0.006**	-0.001	-0.005**
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes
Observations	12,171	10,262	10,430	10,301	10,391
R^2	0.931	0.911	0.961	0.933	0.952

Table 2.13 Alternative Markup and TFP definition

This table presents the difference in differences estimates using S&P500 inclusions of competitors. The dependent variables is Sale over Opex* as alternative proxy for markup (Panel A) and total factor productivity without Olley Pakes correction (Panel B). Firms that are already in the S&P500 index and are in an industry that experiences an addition of a competitor firm to the S&P500 in a given year are the treatment group, and all other firms in different industries that did not experience an inclusion in the index are the control firms. The Post dummy takes value of 1 for the event year and for the three years after the inclusion, and takes value of 0 for the four years before. Additional control variables are Size, Market to Book, Roa, % of Institutional ownership and PP&E, Total debt and Capex scaled by Total Assets. The tables are divided into two sets of columns: (1) to (3) represent estimates from the technological spillover sample, and (4) to (6) represent estimates from the management practice sample. Each regression includes firm fixed effect and year fixed effect. Standard errors clustered at firm level are reported under each estimate in parentheses. Estimates followed by $***$, $**$, and $*$ have p-values lower than 0.01, 0.05, and 0.1.

Panel A: $SALE/OPEX*$

Dependent variable	Log markup					
	Technological spillover			Management practice		
	All	Low	High	All	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
Post x Treated	0.012*	-0.001	0.026***	0.008	-0.003	0.016*
	(0.007)	(0.009)	(0.009)	(0.005)	(0.004)	(0.008)
Post	-0.003*	-0.001	-0.004**	-0.000	0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observation	11,808	10,293	10,042	4,340	3,858	4,003
R^2	0.934	0.920	0.966	0.988	0.990	0.985

Panel B: TFP OLS

Dependent variable	TFP					
	Technological spillover			Management practice		
	All	Low	High	All	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
Post x Treated	0.009	0.005	0.015***	0.013***	0.013*	0.012**
	(0.006)	(0.009)	(0.006)	(0.005)	(0.007)	(0.006)
Post	-0.003	-0.000	-0.003*	-0.000	0.001	0.000
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observation	12,145	10,429	10,135	5,672	4,777	4,534
R^2	0.912	0.891	0.945	0.945	0.923	0.973

APPENDIX

2.A. Measuring productivity

I calculate Total Factor Productivity (TFP) as firm-level Multifactor Revenues Productivity (MFPR). In this context, sales represent the output of the production function, while Capital (K) and a bundle of other inputs (M) represent the inputs. To account for intangible capital accurately, I adopt the approach proposed by Peters and Taylor (2017a). Due to the unavailability of precise wage bill data in Compustat, I utilize a bundle of inputs (M) instead of labor, as suggested in De Loecker et al. (2020a). In this case, I use the cost of goods sold (COGS) as a proxy for M, which encompasses various expenses related to production goods, including materials, energy, intermediate input, and labor costs.

To ensure consistency, all the variables are deflated using the BEA's GDP deflator series. For the analysis, I apply a commonly used Cobb Douglas production function assumption for firm i within the 2-digit SIC sector s in year t, as commonly observed in the literature.

$$Y_{i,s,t} = A_{i,s,t} M_{i,s,t}^{\gamma} K_{i,s,t}^{\beta}$$

The MFPR for each sector s is the residual of the following log regression for each 2–digit SIC industries.

$$y_{i,t} = a_{i,t} + \delta_t + \gamma_s m_{i,t} + \beta_s k_{i,t} + \varepsilon_{i,t}$$

The time dummy δ_t serves to detrend the MFPR estimates. Nevertheless, this procedure may be susceptible to selection and simultaneity biases. Simultaneity arises because firms are aware of their productivity levels when choosing inputs, leading them to increase inputs in response to a positive productive shock. Consequently, OLS estimates may become biased due to unobserved productivity shocks. On the other hand, selection bias occurs due to the relationship between productivity shocks and the probability of exiting the market. Firms with substantial capital stock are generally more profitable and have a higher likelihood of surviving negative productivity shocks compared to firms with low capital stock. This negative correlation between capital stock and the probability of exit could downwardly bias the coefficient of capital.

To address these concerns, I utilize the Olley and Pakes correction, which helps mitigate the issues associated with simultaneity biases and selection biases (Olley and Pakes, 1996). To address the simultaneity problems, I employ investment as a proxy for an unobserved time-varying productivity shock, following the approach outlined in De Loecker et al. (2020a). Specifically, I define Investment as the sum of physical investment (capx) and intangible investment. Additionally, I tackle the selection issues by utilizing survival probabilities.

Another important consideration is the use of revenues as output. While revenues are suitable if prices accurately reflect product quality, they may not fully represent a company's efficiency level if prices incorporate differences in market power. To handle this concern, I control for markups by introducing a linear function of firm sales shares (Baqaee and Farhi, 2019).

Moreover, to minimize the impact of outliers on the productivity function estimates, I exclude firms with COGS-to-sales and XSGA-to-sales ratios in the top and bottom 2.5

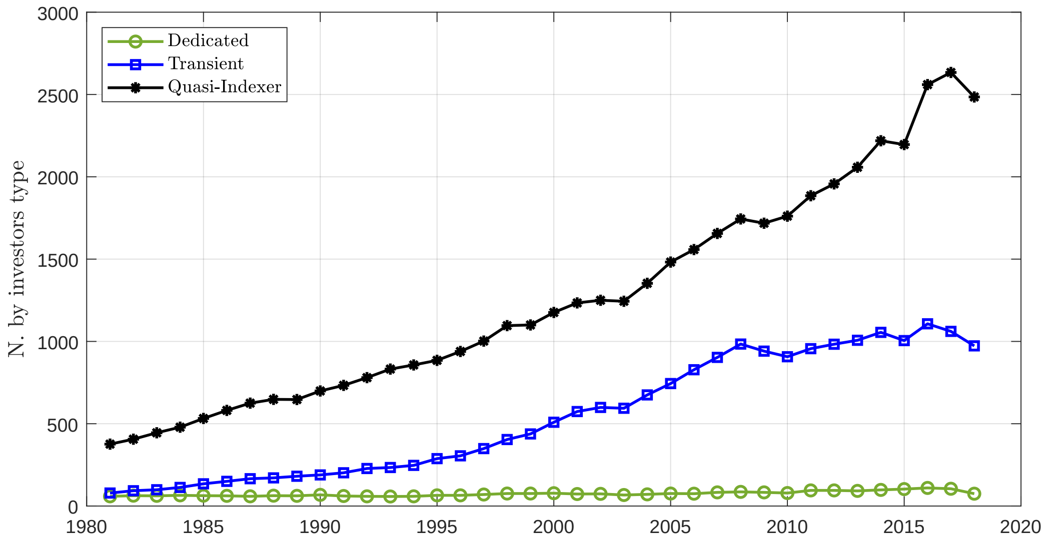

Fig. 2.A.1 **Number of institutional investors by type:** This figure shows the yearly evolution in the number of institutional investors by type. Following Bushee (1998) and Bushee (2001), I disentangle institutional investors into three categories: ”Dedicated”, ”Quasi-indexers” and ”Transient”.

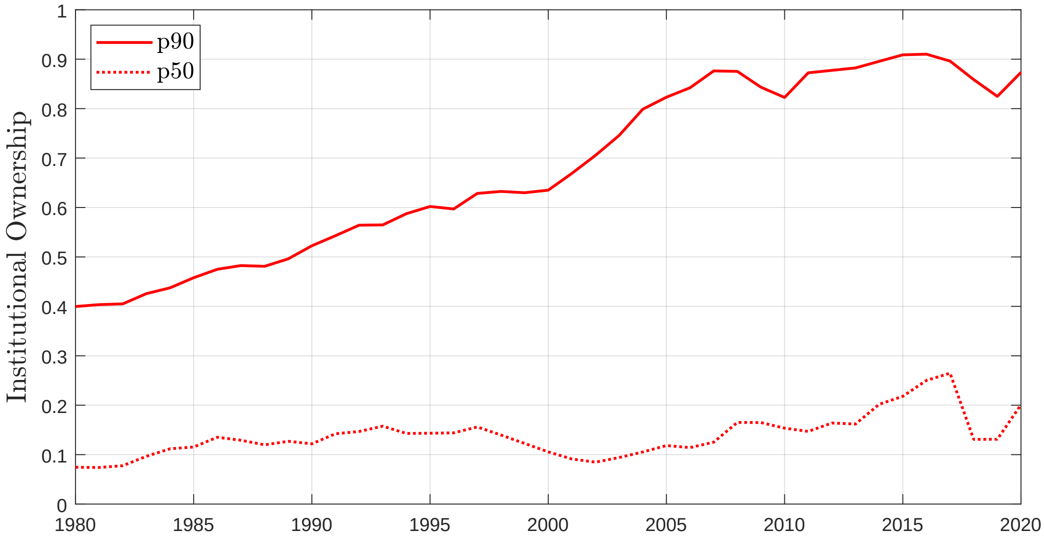

Fig. 2.A.2 Evolution of institutional ownership: This figure shows the yearly p50 and p90 percentiles of institutional ownership distribution from 1980 to 2019.

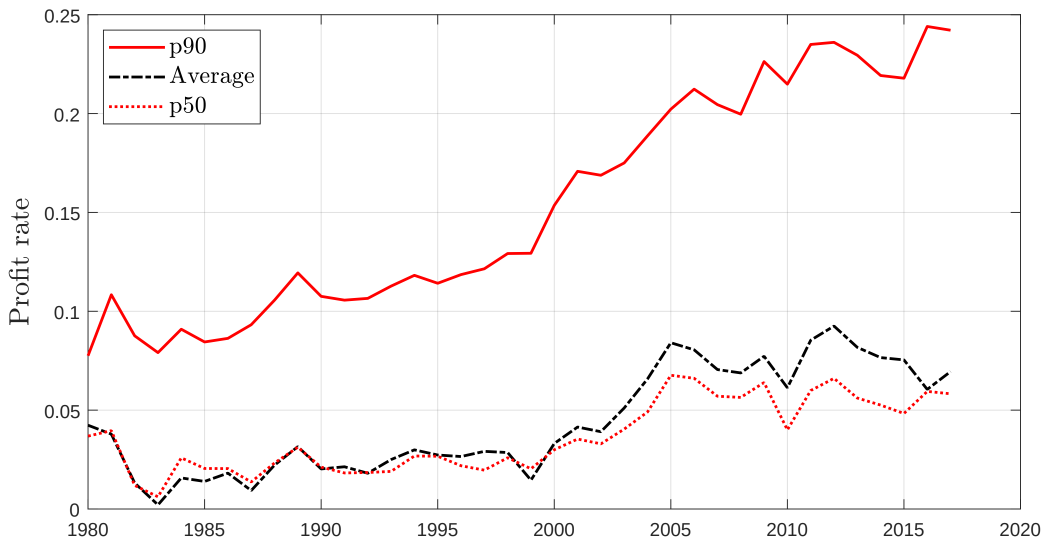

Fig. 2.A.3 Profit rate percentiles over time: This figure illustrates the time series of p50 and p90 of profit rate from 1980 to 2016. The percentiles are revenue weighted. Profit rates are computed following De Loecker et al. (2020a).

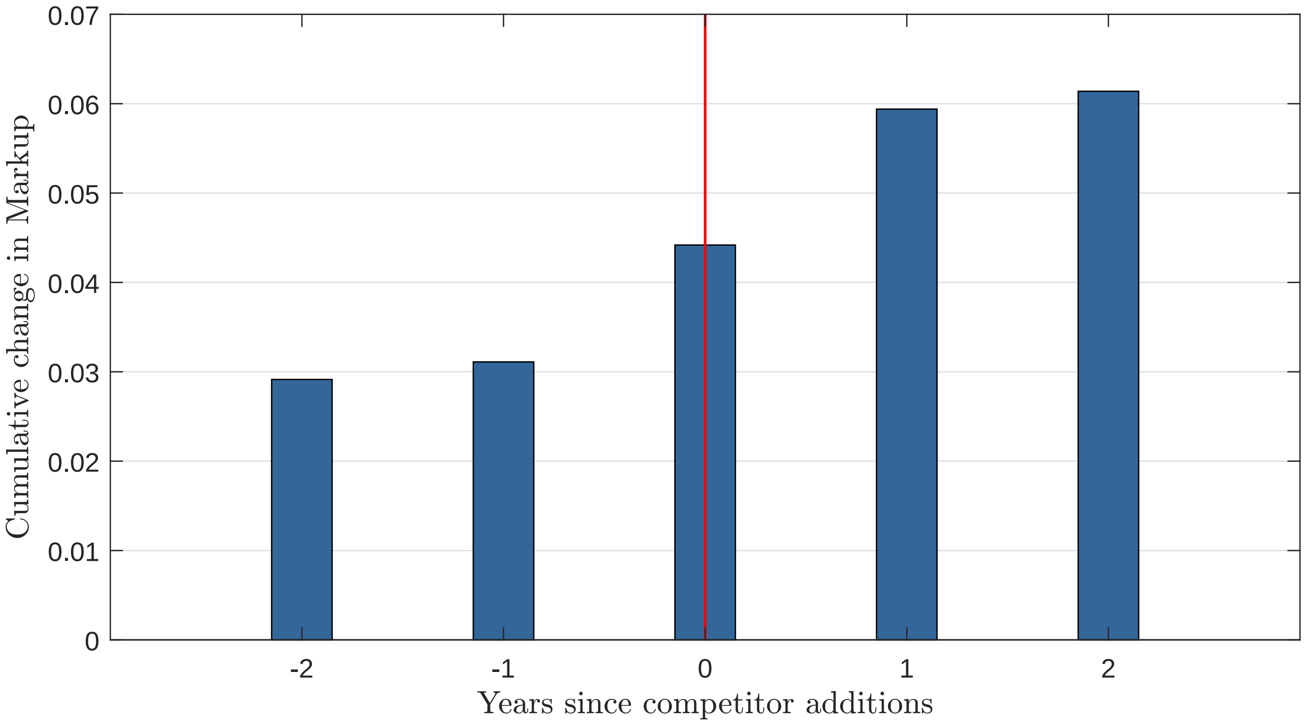

Fig. 2.A.4 Average adjusted change in Markup: The figure represents the Mean-adjusted increase in Markup around the S&P500 competitor addition. For each S&P500 addition, let t be then number of years since the addition. For each t and treated firm, I calculate the markup change from 3 years before the event $(t-3)$ to t. Concurrently, I compute the average markup change between -3 and t for all control firms. The difference between the markup change of treated firms and the average markup change of control firms is then determined. The resulting figure depicts the average adjusted change in Markup for $t-2,-1,0,1,2$.

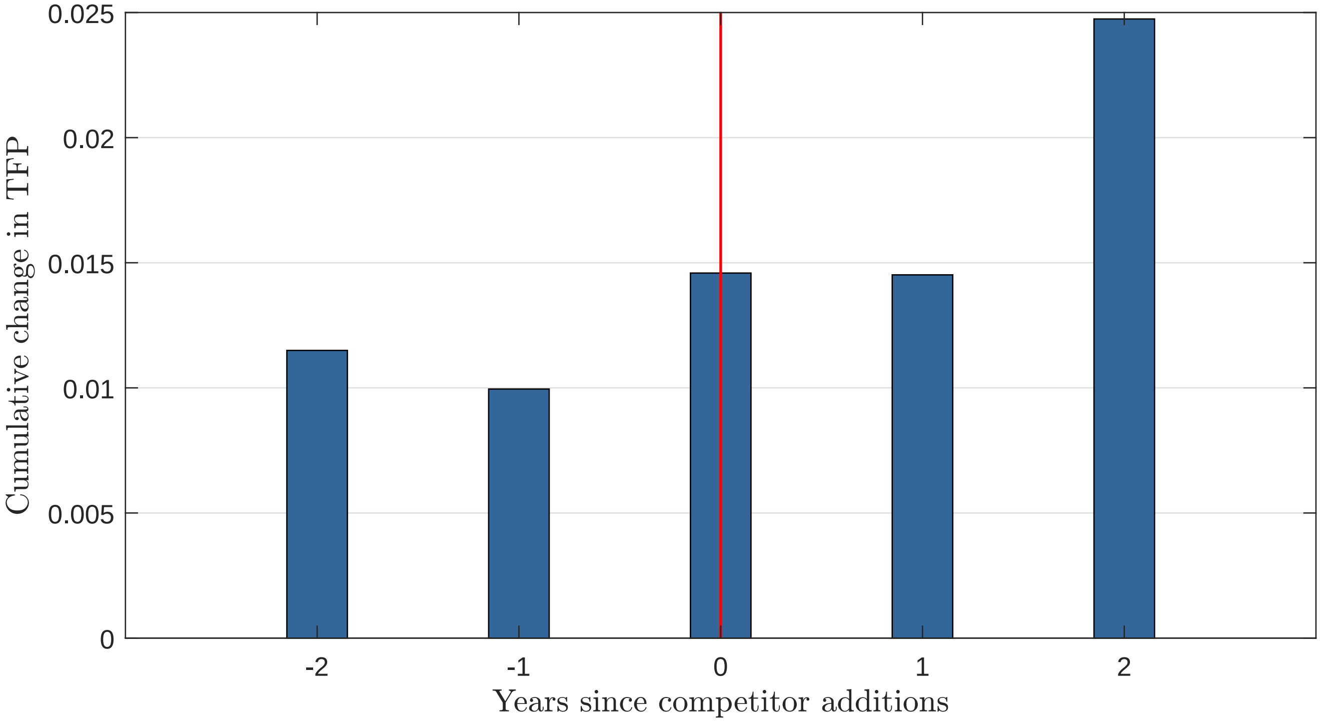

Fig. 2.A.5 **Average adjusted change in TFP:** The figure represents the Mean-adjusted increase in TFP around the S&P500 competitor addition. For each S&P500 addition, let t be then number of years since the addition. For each t and treated firm, I calculate the TFP change from 3 years before the event $(t-3)$ to t. Concurrently, I compute the average TFP change between -3 and t for all control firms. The difference between the TFP change of treated firms and the average TFP change of control firms is then determined. The resulting figure depicts the average adjusted change in TFP for $t-2,-1,0,1,2$.

Company Name	Sector	Total Engagement Count	G - Board Composition & Effectiveness	G - Business Oversight/Risk Management	G - Executive Management	G - Corporate Strategy	G - Governance Structure	G - Remuneration	E - Climate Risk Management	E - Environmental Impact Management	E - Operational Sustainability	S - Human Capital Management	S - Social Risks and Opportunities	Last Engagement Date
3M CO	Industrials	2	1	1	1	1	1	0	1	0	0	0	2	01-Nov-21
AAR CORP	Industrials	1	0	0	0	1	1	0	1	0	1	0	0	07-Sep-21
ABBOTT LABORATORIES	Health Care	2	1	1	0	2	1	0	0	0	0	2	2	06-Dec-21
ABIOMED, INC.	Health Care	1	0	1	0	1	1	0	0	0	1	0	0	28-Jul-21
ACACIA RESEARCH CORP	Industrials	1	0	0	0	0	0	0	1	0	0	0	0	13-Dec-21
ACADIA PHARMACEUTICALS INC	Health Care	1	0	0	0	1	1	1	1	0	1	0	0	06-Jan-21
ACCENTURE PLC	Information Technology	2	1	0	2	0	0	0	0	0	0	1	1	20-Oct-21
ACTIVISION BLIZZARD INC	Communication Services	2	0	0	0	0	0	0	0	0	2	1	1	04-Jun-21
ADTALEM GLOBAL EDUCATION INC	Consumer Discretionary	1	1	0	1	1	0	0	1	0	0	1	0	06-Apr-21
ADVANCED MICRO DEVICES INC	Information Technology	1	0	1	1	0	0	0	0	0	0	1	0	12-Feb-21
AECOM	Industrials	1	0	0	0	0	0	0	0	1	0	0	0	10-Feb-21
AES ANDES SA	Utilities	1	1	1	1	1	1	0	0	1	0	1	1	09-Apr-21
AES CORPORATION (THE)	Utilities	1	1	0	0	1	0	0	0	0	0	0	0	13-Dec-21
AFFILIATED MANAGERS GROUP INC.	Financials	1	1	1	1	0	0	0	1	0	1	0	0	03-Dec-21

Fig. 2.A.6 BlackRock Engagement: This figure reports an extract of BlackRock's stewardship engagement activity in 2021 (BlackRock report 2021).

Table 2.A.1 Definitions and descriptive of variables
This table presents the definitions of the main variables used in the analysis.

Variable name	Variable definition
Markup	Marginal cost markup by De Loecker et al. (2020a)
Markup (Opex)	SALE/(OPEX-&D- RDIP)
TFP	TFP computed with Olley Pakes corrections as described in Appendix 2.A
Investment efficiency	Residual of Investment on Tobin Q regression plus a set of controls following Richardson (2006)
R&D	R&D / Invested capital
Output	Sales / Invested capital
Size	Logarithm of total assets (AT)
Size Growth	$\text{Size}_t - \text{Size}_{t-1}$
Market to book	(PRCC F x CSHO) / CEQ
Roa	Net income (NI) / Total assets (AT)
Cash holdings	Cash (CHE) / Total assets (AT)
PP&E/Assets	PPENT/AT
Total debt/Assets	(DLC + DLTT)/AT
Capex/Assets	CAPEX/AT
Invested capital	PPENT + ACT + ICAP - LCT - GDWL - max(CHE-0.02 x SALE, 0)
Capital (K)	Stock of tangible plus intangible capital, computed as in Peters and Taylor (2017a)
Bundle of inputs (M)	proxied by COGS as in De Loecker et al. (2020a)
Investment	Investment in tangible & intangible assets, as defined by Peters and Taylor (2017a): Capex + R&D expense + 0.3 × SG&A expenses scaled by Capital
Tobin Q	by Peters and Taylor (2017a)
% Institutional holdings	Total number of shares held by institutional investors from Thomson 13F / Shares outstanding
Num. connections	Number of unique peers that share at least one QIX institutional investor with a share greater or equal than 0.5%
N. engagement	Number of times the BIS engage with a firm in a year
S&P 500 member	1 if a firm is a member of the S&P500, 0 otherwise
Technological spillover	by Bloom et al. (2013)
Management practice	by Bloom and Van Reenen (2007)
Knowledge Capital	by Peters and Taylor (2017a)
Organizational Capital	by Peters and Taylor (2017a)

Table 2.A.2 **Industry technological spillover and management practice**

This table reports the industry-level averages of the two economic mechanism variables: technological spillovers (in ten thousand), management practices. Industry j's technological spillover (management practices) are the cross-sectional median of all firms' technological spillover (management practice). Management practices data are available just for manufacturing firms, I exclude firms with less than 500 employees to obtain a better proxy of management practice in listed firms. I keep state-industry-year with at least 10 observations. After this adjustment, I end up with a panel covering 29 industries.

	Technology spillover	Management Practices
10	2.091662	
13	1.836679	
20	1.255474	3.375
22	.5001203	3.555556
23	.6614887	3.090278
26	1.641609	3.407407
27	.4837476	3.277778
28	3.557598	3.277778
29	1.555389	3.148148
30	1.143925	3.481481
32	.9246269	3.111111
33	1.658802	3.407408
34	1.369205	3.222222
35	1.898587	3.458333
36	2.048493	3.722222
37	1.823333	3.462963
38	1.867619	3.638889
39	.4370341	3.486111
48	2.711985	
50	.6872934	
51	.734377	
54	.3358406	
58	.8665298	
59	1.599613	
73	1.585479	
78	1.745927	
79	.4085686	

Table 2.A.3 S&P 500 Competitor addition, Common and Institutional ownership
This table presents estimates from panel regressions of number of connections in logarithmic form via QIX common owners (Column 1 to 3) and the total percentage of institutional ownership (Column 4 to 6) on a dummy variable that takes value 1 if a competitor is added to the S&P500 and 0 otherwise. Additional control variables are Size, Market to Book, Roa, % of Institutional ownership and PP&E, Total debt and Capex scaled by Total Assets. Each regression includes firm fixed effect and year fixed effect. Standard errors clustered at firm level are reported under each estimate in parentheses. Estimates followed by $***$, $**$, and $*$ have p-values lower than 0.01, 0.05, and 0.1.

Dependent variable	Log N. connections			% Inst. Ownership		
	(1)	(2)	(3)	(4)	(5)	(6)
S&P500 Competitor addition	0.064***	0.052***	0.052***	-0.004	-0.006**	-0.008***
	(0.014)	(0.014)	(0.012)	(0.003)	(0.003)	(0.002)
Size		0.103**	-0.029		0.104***	0.003
		(0.043)	(0.050)		(0.006)	(0.007)
Market to book		0.023***	-0.008		0.005***	-0.003**
		(0.007)	(0.006)		(0.002)	(0.001)
Roa		-0.337***	-0.035		0.005	0.051**
		(0.121)	(0.121)		(0.029)	(0.023)
PP&E/Assets		0.014	-0.116		-0.107**	0.028
		(0.249)	(0.201)		(0.042)	(0.032)
Total debt/Assets		-0.171	-0.172		-0.091***	-0.029
		(0.135)	(0.126)		(0.031)	(0.025)
Capex/Assets		0.429	0.762**		-0.088	0.181***
		(0.419)	(0.349)		(0.069)	(0.061)
% Inst. Ownership		0.457***	-0.023			
		(0.145)	(0.162)			
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,368	10,581	10,581	13,060	11,550	11,550
R^2	0.002	0.052	0.244	0.000	0.279	0.540

Table 2.A.4 Production costs

This table presents the difference in differences estimates using S&P500 inclusions of competitors. The dependent variable is Production cost computed as Cogs over invested capital. Firms that are already in the S&P500 index and are in an industry that experiences an addition of a competitor firm to the S&P500 in a given year are the treatment group, and all other firms in different industries that did not experience an inclusion in the index are the control firms. The Post dummy takes value of 1 for the event year and for the three years after the inclusion, and takes value of 0 for the four years before. Panel A reports the results for technological spillover sample and panel B for the management practice sample. Firm controls include: Size, Market to Book, Roa, % of Institutional ownership and PP&E, Total debt and Capex scaled by Total Assets. Each regression includes firm fixed effect and year fixed effect. Standard errors clustered at firm level are reported under each estimate in parentheses. Estimates followed by $***$, $**$, and $*$ have p-values lower than 0.01, 0.05, and 0.1.

Panel A: Technological spillover

Dependent variable	Production costs					
	Technological spillover					
	All (1)	Low (2)	High (3)	All (4)	Low (5)	High (6)
Post x Treated	-0.006	-0.006	-0.004	-0.007	-0.009	-0.004
	(0.006)	(0.008)	(0.006)	(0.006)	(0.009)	(0.006)
Post	0.006**	0.007**	0.005*	0.010***	0.011***	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	No	No	No	Yes	Yes	Yes
Observations	15,375	13,139	12,860	12,148	10,429	10,138
R^2	0.936	0.932	0.942	0.947	0.943	0.961

Panel B: Management practice

Dependent variable	Production costs					
	Management practice					
	All (1)	Low (2)	High (3)	All (4)	Low (5)	High (6)
Post x Treated	0.006	0.007	0.007	0.007	0.009	0.009*
	(0.007)	(0.010)	(0.006)	(0.007)	(0.010)	(0.005)
Post	-0.000	0.000	-0.001	0.002	0.002	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	No	No	No	Yes	Yes	Yes
Observations	6,238	5,251	4,991	5,672	4,777	4,534
R^2	0.955	0.951	0.974	0.964	0.961	0.984

Chapter 3

How do Firms choose between growth and efficiency?*

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3.1. Introduction

A long standing idea in the corporate world is that most firms face a strategic choice between growth and efficiency, as they cannot easily grow and become efficient at the same time. For instance, management consultants and strategic experts routinely advise firms to either pursue a "growth strategy" and allocate resources and effort to increase their scale and revenues, or instead choose an "efficiency strategy" focusing on rendering firms' operations and capital more efficient and eliminating waste.[1] When valuing companies, analysts and investors consider both growth and efficiency as value drivers but typically predict them independently. Conventional wisdom and life cycle arguments also suggest that firms should "pivot" from growth to efficiency as they mature.

While the tug of war between growth and efficiency appears central in practice, existing research in corporate finance provides limited insights regarding how firms should choose between these strategies. In particular, little is known about whether there is an optimal balance between them, when to pivot, what are the economic drivers of these strategies, and their potential long-term consequences (e.g., firms' resilience to shocks, survival or success). This limitation arises because researchers typically do not consider efficiency as something firms

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[1]See for instance: "Profit vs Growth: What is the Correct Strategy for Your Business? in *Forbes*, December 2018, or "Stop Focusing on Profitability and Go for Growth" in *Harvard Business Review*, May 2017.

choose, but treat it as exogenous (i.e., a shock). For instance, in models following the neoclassical tradition, growth results from firms' choice of productive inputs (e.g., capital and labor), given an *exogenous* level of efficiency. Thus, firms' efficiency is treated and measured as a "residual", making it difficult to understand its economic determinants. To shed light on how firms choose between growth and efficiency, we take a different approach: we consider that efficiency is not a residual but a *choice* and we propose a novel empirical methodology to estimate this choice from the data.

To do so, we consider a dynamic model in which a firm chooses capital and labor inputs *jointly* with the level of efficiency. The firm employs capital and labor to generate earnings, but can also choose the level of effort exerted to make these inputs more productive.[2] We explicitly view efficiency as a problem of costly effort provision, whereby the firm can increase current earnings by exerting "efficiency effort" (for a given level capital and labor). Efficiency effort can include, for instance, monitoring employees, increasing managers' attention, enforcing contracts, coordinating activities, updating plans, or nurturing relationships with various business partners. We further posit that the effects of such effort only last one period, so that efficiency effort has to be exerted every period to affect earnings. Hence, unlike the choice of capital and labor, effort to increase efficiency does not affect the firm's growth.

Our first contribution is to measure firms' unobservable level of efficiency effort from the data. The model's solution describes the firm's optimal capital investment, labor growth and efficiency effort in closed form, as a result of the trade-offs between the marginal benefits and costs of adjusting each factor or exerting effort. Higher levels of effort increases the firm's productive efficiency and makes the firm more valuable. This in turn increases the marginal benefit of investment and labor. Therefore, efficiency effort, investment, and hiring decisions are complements in the earnings function for any given firm, and their allocation depends on their relative adjustment costs. Using the model, we show that the firm's optimal efficiency effort can be identified as a function of its *observed* investment and labor growth paths and the time series of its operating earnings.

We estimate the model for over 12,000 U.S. public firms between 1971 and 2019 using an Unscented Kalman filter with Maximum Likelihood. This procedure, which follows from the non-linear nature of production and optimal policies, has three main advantages: (i) it takes into account the measurement error in the observed inputs, (ii) it uses time consistent policies, and (iii) it uses the explicit closed form dynamics of latent capital and labor based on the model equilibrium growth path. We can estimate the model (14 parameters) at a very granular level by forming groups composed of homogeneous firms (i.e., exposed to similar shocks). Each group represents an unbalanced panel reflecting firms' entry and exit from the sample. This granular estimation enables us to describe the optimal allocations of investment (in tangible

[2]In that respect, the model resembles recent dynamic agency models in which managers can also directly affect firms' earnings either by exerting unobserved effort or by consuming private benefits (e.g., DeMarzo and Sannikov (2006)).

and intangible capital), hiring, and efficiency effort across groups of firms within industries and over time.

We start by estimating the model for the whole sample period across 1,346 distinct groups of ten firms based on their cohort (i.e., the decade of their IPO), industry, and earnings growth rates, obtaining group-specific (time-invariant) parameters. The average parameter estimate for investment in tangible and intangible capital is 20% (of lagged capital). The average efficiency effort amounts to 0.29. This quantity represents the average expected earnings per efficient units of capital and labor. We find a large heterogeneity in both efficiency effort and investment across groups, and a negative correlation between these estimated parameters. That is, firms choose very different allocations of efficiency and growth. Consistent with firms pivoting from growth to efficiency as they mature, the ratio of efficiency to investment (capturing the relative importance of efficiency over growth) is significantly higher for earlier cohorts that are predominantly composed of older firms (i.e. firms entering in the 70s or 80s that are still active).

To better characterize firms' dynamic choices of efficiency and growth and analyze their consequences, we re-estimate the model separately during firms' IPO decade and the next, and further distinguish between firms that exit due to bankruptcy during their IPO decade and firms that survive it (or were acquired during it). This more granular estimation (6,270 distinct groups) enables us to account for changes in the composition of the sample. Focusing on firms' first decade, firms' entering the sample older focus more on efficiency and less on growth, irrespective of their survival status, cohort, or industry. For survivors, firms with more volatile shocks to their capital stock focus less on growth, while firms investment with higher elasticity of earnings to capital focus less on efficiency. Focusing on surviving firms, we confirm that the ratio of efficiency to investment increases significantly from firms' IPO decade to the next. This increase is present across cohorts and industries, and ranges between 15% for firms in manufacturing to 36% for firms in consumer goods. The shift from growth to efficiency also holds after we control for the other estimated parameters (e.g., the elasticity of earnings to capital or the volatility of shocks to firms' capital stock) as well as firms' age when they enter the sample.

Next, we use the parameters estimates to examine whether firms' choices of efficiency and growth while young predicts outcomes as they mature. They do. In particular, we find that the ratio of efficiency over investment is strongly related to firms' survival. Across all cohorts and industries, surviving firms display a higher ratio of efficiency over growth in their first decade compared to non-surviving firms. Further highlighting the relevance of efficiency effort for survival, we re-estimate the model around the 2008 great financial crisis and show that firms that did not survive the crisis focused much more on growth and less on efficiency in the years preceding it.

Conditional on surviving their firms decade, firms' choices of efficiency and growth while young also predict their future performance.

Overall our results indicate that firms focused on growth when young achieve the highest performance in the long-term, whereas firms focused on efficiency have higher chances of surviving in the long-term.

Our paper primarily adds to the sparse literature studying firms' choice between growth and efficiency strategies. The idea that firms may have to choose between these strategies is not new and popular in practice. Yet it is only found in distinct pockets of the literature. For instance, Loderer et al. (2017) informally rely on this idea to explain why firms' valuation (their Tobin's Q) declines as they mature. This idea is also indirectly present in papers focusing on the trade-off between exploration and exploitation (e.g., Holmstrom (1989) or Manso (2011)).[3] To shed new light on how firms choose between growth and efficiency, we take a more direct road and develop a neoclassical model in which firms separately choose growth and their level of operating efficiency. We then use the model to estimate the unobservable level of firms short-term efficiency-boosting effort. We use these new estimates to characterize the determinants and implications of firms' growth and efficiency strategies.

The paper also adds to the recent work studying how firms' decisions and performance vary over their life cycles. Loderer et al. (2017) show that, as firms age, they have less growth opportunities, become more rigid and less able to respond to growth opportunities. Arikan and Stulz (2016) report that firms' acquisition rate changes over their life cycle, and follows a U-shaped pattern with respect to age. Focusing on firms' product life cycles Hoberg and Maksimovic (2021) indicate that firms invest in intangible and tangible capital early in their cycle, acquire assets as they mature, and divest as they decline. Bustamante et al. (2021) examine firm's investment over their knowledge cycles. We complement these studies by studying firms' decision to focus on growth or efficiency, estimate firms' choice of efficiency, and show that it varies over their life.

The paper also belongs to a stream of recent models in the neoclassical tradition that allow firms to influence their profits directly, outside of their choice of production inputs (i.e., different types of capital and labor). Specifically, Hackbarth et al. (2021) and Gryglewicz et al. (2020) also consider that firms can exert efficiency effort to study the impact of permanent and transitory shocks on optimal compensation and investment in dynamic moral hazard models. We use a similar modelling approach, but study instead firms' decision between growing or becoming more efficient. Unlike these papers, we also develop a framework to estimate the unobservable level of firms' efficiency, and analyse empirically its determinants. Methodologically, our model's estimation resembles that used by Gryglewicz et al. (2022) to disentangle empirically the permanent and transitory shock of firms' cash flows.

The structure of the paper proceeds as follows. Section 3.2 presents the firm model and derives the optimal policies. Section 3.3 discusses the estimation method and data. In Section 3.4

[3] In this context, "exploration" could be associated with the strategy of growing a firm's assets, whereas "exploitation" corresponds to the strategy of making these assets more productive.

we describe our estimation results. Section 3.5 focuses on growth versus efficiency choices. Section 3.6 presents an empirical asset pricing application as a validation of our estimates. Section 3.7 concludes. The appendix collects technical derivations.

3.2. Model

Managers make decisions on behalf of risk neutral shareholders that discount cash flows at a constant rate $r > 0$. Time is continuous and uncertainty is modeled by a filtered probability space $(\Omega, \mathscr{F}, \mathbb{F}, Q)$ satisfying the usual conditions.

3.2.1. Earnings

The firm employs capital and labor to produce earnings. The capital stock K_t evolves according to the controlled process

$$dK_t = (i_t - \delta_K)K_t\,dt + \sigma_K K_t\,dW_{K,t} \tag{3.1}$$

where $i_t \in [0, i_{\max}]$ is the firm's investment choice and $\delta_K > 0$ is the depreciation rate. The growth of the capital stock also has a random component, with constant volatility $\sigma_K > 0$ and shocks drawn off a standard Brownian motion $W_{K,t}$. Similarly, the total work force L_t evolves as

$$dL_t = (h_t - \delta_L)L_t\,dt + \sigma_L L_t\,dW_{L,t} \tag{3.2}$$

where $h_t \in [0, h_{\max}]$ is the firm's hiring choice and $\delta_L > 0$ is the separation rate, that is, the expected percentage of employees that resign, retire or are laid off each period. Shocks to the growth rate of the work force are drawn from a standard Brownian motion $W_{L,t}$. The constant volatility of the work force growth rate is $\sigma_L > 0$. Because shocks are to the growth rates of capital or labor, they have permanent effects on firm value. We interpret these effects as embodied technological progress or training of the work force.

Operating earnings over the time increment dt are given by a Cobb–Douglas function with decreasing returns to scale, $K_t^\gamma L_t^\beta\,dA_t$, in which $0 < \gamma < 1$ and $0 < \beta < 1$ are the elasticity of earnings to capital and labor, and $\gamma + \beta \le 1$. The A_t process is the firm's efficiency level, which is *controlled* by the choice of efficiency, $e_t \in [0, e_{\max}]$, and evolves according to

$$dA_t = e_t\,dt + \sigma_A\,dW_{A,t}. \tag{3.3}$$

Efficiency also has a random component, captured by an additive standard Brownian motion shock $W_{A,t}$, scaled by the constant volatility $\sigma_A > 0$. Thus, the firm sets the expected efficiency in operating the mix of capital and labor by exerting a flow of effort period by period. Like the other inputs, higher levels of e_t imply higher earnings. Unlike K and L, e_t is not cumulative: it has a rate of depreciation of 100% and, therefore, does not directly contribute to the firm's growth. As examples of policies included in e_t, consider advertising campaigns, inventory management, contract renegotiation, or day-to-day monitoring of plant- or employee-level productivity. For all these examples, their effects on current earnings would disappear quickly if such policy were stopped. Note too that earnings can be negative if and only if dA_t is negative.[4]

The earnings model in (3.1)–(3.3) nests popular models in the literature. We can recover the stationary cash flow process of the dynamic agency models by DeMarzo and Sannikov (2006) or DeMarzo et al. (2012) and the liquidity management models of Décamps et al. (2011) and Bolton et al. (2011) by setting $i_t - \delta_K = \sigma_K = 0$, so that the capital stock is constant, $\gamma = 1$ to have constant returns to scale for capital, and $\beta = 0$ to remove the labor factor. We recover the model with time-varying profitability used by Leland and Toft (1996), Leland (1998), Goldstein et al. (2001), Hackbarth et al. (2006), or Strebulaev (2007) to discuss dynamic capital structure, or by Abel and Eberly (1994) or Carlson et al. (2004) to analyze real-options, if we set $\sigma_A = 0$, to rule out shocks with short-term effects, $i_t - \delta_K$ to a constant, $\beta = 0$, and $\gamma = 1$. A general structure, which allows for randomness in earnings directly or via input growth rates, is desirable because, in reality, shocks exist that change the firm's long-term prospects while other shocks are instead temporary and subside over time. The combination of the two types of shocks is in fact a necessity: Gorbenko and Strebulaev (2010) and Gryglewicz et al. (2022) show that the cashflow model including *both* shocks with short-term and permanent effects can simultaneously match the earnings and assets volatilities of Compustat firms, whereas models with either type of shock cannot.

3.2.2. Input adjustment costs

As for the capital stock or the labor force, adjusting efficiency is increasingly costly. We consider the following quadratic adjustment cost function

$$C(e_t, i_t, h_t, K_t, L_t) = \left(\frac{\lambda_e}{2}e_t^2 + \frac{\lambda_K}{2}i_t^2 + \frac{\lambda_L}{2}h_t^2\right)K_t^{\gamma}L_t^{\beta} \tag{3.4}$$

where the parameters $\lambda_e, \lambda_K, \lambda_L$ are strictly positive. The convexity of this function captures the notion that there are additional frictions to implementing a higher level of efficiency. For example, a higher level of efficiency may involve introducing a more complex supply chain or inventory model, implementing a new marketing campaign, or engaging in renegotiation of contracts with a larger, more diversified, network of clients and providers. This function may also account, in a reduced form, for the additional costs of contracting optimally. Because the model does not explicitly account for agency conflicts with management, the parameter λ_e also includes the cost of giving management the right incentives to exert optimal short-term

[4] As dA_t can take negative values, its exponent is set to one.

efficiency.

As in Hayashi (1982b), the cost function is homogeneous of degree one in $K_t^\gamma L_t^\beta$ and depends on the investment and hiring rates rather than their levels. In the appendix we consider more general cost functions in which capital and labor are cost complements or substitutes. The model solution derived below is robust to these alternative specifications of the cost function.

3.2.3. Firm policies

Management chooses efficiency, investment and hiring policies to maximize firm value, which is given by the expected discounted flow of earnings net of adjustment costs. With two state variables, K_t and L_t, we can write the maximization problem as

$$V(K_0, L_0) = \sup_{e,i,h} \mathbb{E} \int_0^\infty \exp(-rt) \left(K_t^\gamma L_t^\beta dA_t - C(e_t, i_t, h_t, K_t, L_t)\, dt \right) \tag{3.5}$$

where the expectation $\mathbb{E}$ is conditional on the starting values of capital and labor, K_0 and L_0, and $e_{\max}$, $i_{\max}$, $h_{\max}$ are large enough to ensure that the solution is interior at all times. Standard arguments yield that the firm value V satisfies the following Hamilton–Jacobi–Bellman (HJB) equation

$$\begin{aligned} rV(K,L) = \sup_{e,i,h} \{ & K^\gamma L^\beta e - C(e,i,h,K,L) + V_K(i-\delta_K)K + V_L(h-\delta_L)L \\ & + \frac{1}{2} V_{KK} \sigma_K^2 K^2 + \frac{1}{2} V_{LL} \sigma_L^2 L^2 \} \end{aligned} \tag{3.6}$$

where V_x and V_{xx} denote, respectively, the first- and second-order derivatives of $V(K,L)$ with respect to $x = K, L$. The left-hand side of this equation represents the required rate of return for investing in the firm's equity. The right-hand side is the expected change in equity value along the equilibrium path. The first two terms are the expected earnings net of adjustment costs. The next two terms are the effects of expected changes in capital $(i-\delta_K)K$ and labor $(h-\delta_L)L$ on changes in equity value. The last two terms are the effects of volatility of capital and labor on changes in equity value.

Firm's policies are obtained by solving the system of first-order conditions to (3.6). We show in Appendix 3.A.1 that the solution to the value function $V(K,L)$ is $cK^\gamma L^\beta$, where the constant c is a function of the model's primitives γ, β, λ_e, λ_K, λ_L, δ_K, δ_L, σ_K, σ_L, and that the optimal policies are

$$e^* = \frac{1}{\lambda_e}, \qquad i^* = c\frac{\gamma}{\lambda_K}, \qquad h^* = c\frac{\beta}{\lambda_L}. \tag{3.7}$$

The optimal level of efficiency, e^*, is constant along the equilibrium growth path and inversely related to its marginal adjustment cost, λ_e. The optimal investment and hiring rates, i^* and h^*, are each increasing in c and in the earnings elasticities of capital and labor, but decreasing with their marginal adjustment costs. Higher levels of efficiency make the firm more valuable, which in turn increases the marginal benefit of investment. Hence, lower λ_e imply higher optimal efficiency and, therefore, a higher optimal investment rate. The left panel of Figure 3.1 plots the different combinations of optimal i^* and e^* as λ_e varies. For the blue or black lines, along which all other parameters are kept constant, i^* and e^* are positively correlated. However, keeping λ_e constant, a decrease in the earnings elasticity of capital (from $\gamma = 0.4$ black line, to $\gamma = 0.3$ blue line) reduces optimal investment. Therefore, even if efficiency and capital investment are complements in the earnings function for any given firm, the optimal combinations of efficiency and investment rates in the cross section could be negatively correlated if, for example, λ_e and γ were inversely related across firms.

The right panel of Figure 3.1 shows the optimal combinations of efficiency and investment for different efficiency adjustment costs and volatility of shocks to the capital stock, σ_K. Along the black line, σ_K is a relatively low 0.15; for the blue line σ_K is higher: 0.35. Again, if efficiency adjustment costs and capital shocks volatility were negatively correlated across firms, then so would be efficiency and investment, despite being earnings complements.

3.2.4. Discussion

The primary goal of the model above is to estimate the joint cross-sectional distribution of the three equilibrium policies, e^*, i^*, and h^*. The model ought to be viewed as a minimalist benchmark that allows for robust inference of these policies across most Compustat firms. Appendix 3.A.2 shows that inference is robust to other more general specifications of the model. For example, we can identify the same policies if we allow capital and labor inputs to be complements or substitutes (Appendix 3.A.2), or if shocks to capital and labor stocks are correlated (Appendix 3.A.2), or if we included also linear adjustment costs to capture disinvestment (Appendix 3.A.2), or if firms randomly exit Compustat because of, e.g., default or merger and acquisition (Appendix 3.A.2).

The Cobb–Douglas specification above implies that efficiency is complementary to either investment or hiring in the earnings function. However, whether efficiency and investment or hiring policies are positively or negatively correlated across firms *in equilibrium* depends also on how the adjustment costs function parameters and the capital and labor stocks volatilities are jointly distributed in the cross-section. Some of these deep parameters, namely such as the shocks volatilities and earnings elasticities of the capital and labor stocks, are also identified in the benchmark or richer models.

Identification of the adjustment costs function parameters, i.e., the λ coefficients, will generally require imposing additional structure. Moreover, the input adjustment costs in this benchmark model serves as a reduced form for all the possible frictions to all policies. To make inference about the magnitudes of a particular friction, e.g., agency costs, the researcher would need to ‘open up’ this function and specify its structure explicitly. This task goes beyond the scope of this paper, but we believe it is a feasible step to take in future research.

3.3. Estimation and Data

We describe in this section our method to estimate the model's policies and parameters at a high level of granularity using the time series of earnings, investment, hiring, and capital and labor stock. While firm-by-firm estimation is not feasible, for example because of data scarcity, we are able to estimate different parameter vectors, each for the representative firm of small, homogeneous group.

3.3.1. Equilibrium dynamics

Plugging the optimal firm's policies in the dynamics of capital, labor and short-term shocks, i.e., substituting (3.7) into (3.1)–(3.3), gives the controlled dynamics of these processes. Along the equilibrium growth path, capital and labor stocks follow geometric Brownian motions

$$dK_t = (i^* - \delta_K)K_t\,dt + \sigma_K K_t\,dW_{K,t} \tag{3.8}$$

$$dL_t = (h^* - \delta_L)L_t\,dt + \sigma_L L_t\,dW_{L,t} \tag{3.9}$$

while the the firm's efficiency level follows an arithmetic Brownian motion

$$dA_t = e^*\,dt + \sigma_A\,dW_{A,t}. \tag{3.10}$$

Equations (3.8) to (3.10) describe the optimal time series trajectories of each controlled variable as a function of the model parameters, via their effect on efficiency, investment and hiring policies.

3.3.2. Estimation

Estimation of equations (3.8) to (3.10), together with the Cobb–Douglas earnings function faces several challenges. First, any period's earnings are simultaneously hit by shocks with short- and long term-effects and these must be separately identified. Second, capital and labor stocks data are subject to measurement errors. Unaddressed, this errors-in-variables problem would result in inconsistent estimates of the model's parameters. Third, Compustat earnings data are plagued by missing values. Relative to complete panels which we use for estimation, more than 50% of data are missing. Fourth, operating earnings are non-linearly related to capital and labor through the Cobb–Douglas production technology.

These issues cannot be fixed by taking logarithms. Earnings are negative at the firm level. K and L are not givens but policies and precisely measured with error. Treats residual as exogenous and uses no information about schock structure. We propose instead an efficient estimator that addresses all of these problems: maximum likelihood with an unscented Kalman filter. In what follows, we describe the steps of this procedure for the case of a complete data set. Appendix 3.B provides the full details, including the case in which there are missing observations.

The first step is to write the model in state space form. The transition equation is two-dimensional and describes the discrete-time dynamic of the state variables

$$\log(K_{t+1}) = \log(K_t) + \mu_K + w_{1,t}, \tag{3.11}$$

$$\log(L_{t+1}) = \log(L_t) + \mu_L + w_{2,t}, \tag{3.12}$$

where $\mu_K \equiv i^* - \delta_K - \sigma_K^2/2$ is the drift of the capital stock, $\mu_L \equiv h^* - \delta_L - \sigma_L^2/2$ is the drift of the labor stock, $\mathbf{w}_t = [w_{1,t}\ w_{w,t}]'$ is the vector of transition errors, with $\mathbf{w}_t \sim \mathscr{N}(\mathbf{0}, \mathbf{Q})$ and $\mathbf{Q}$ a diagonal covariance matrix with entries σ_K^2 and σ_L^2. The time step from $t-1$ to t is one year. Because each state variable follows a geometric Brownian motion, the transition equation above is an exact discretization of the continuous-time dynamic. The measurement equations are given by

$$z_{1,j,t} = e^* K_t^{\gamma} L_t^{\beta} + v_{1,j,t} \tag{3.13}$$

$$z_{2,j,t} = K_t + v_{2,j,t} \tag{3.14}$$

$$z_{3,j,t} = L_t + v_{3,j,t} \tag{3.15}$$

$$z_{4,j,t} = i^* K_t + v_{4,j,t} \tag{3.16}$$

$$z_{5,j,t} = h^* L_t + v_{5,j,t} \tag{3.17}$$

where $z_{1,j,t}, \ldots, z_{5,j,t}$ are, respectively, the noisily observed operating earnings, capital stock, labor stock, investment and hiring of firm j in year t. The measurement errors, $v_{1,j,t}, \ldots, v_{5,j,t}$ have variances $\sigma_{v1}^2, \ldots, \sigma_{v5}^2$. We let this set of equations and parameters represent a set of firms $j = 1, \ldots, N$. Therefore, the vector of measurement errors for each group of N firms, $\mathbf{v}_t$, is $5N$-dimensional with $\mathbf{v}_t \sim \mathscr{N}(\mathbf{0}, \mathbf{R})$ and $\mathbf{R}$ a diagonal covariance matrix. Altogether, this state space model has 14 parameters: three related to firm policies, e^*, i^*, h^*, six to deep parameters, γ, β, μ_K, μ_L, σ_K, σ_L, and five for the variances of the measurement errors, $\sigma_{v1}^2, \ldots, \sigma_{v5}^2$.

Estimation at the firm level is unfeasible because the earnings' time series are too short: In our Compustat panel, the operating earnings series are on average (median) only 10.8 (8) years long. To achieve high granularity we follow the same approach as in Gryglewicz et al. (2022): To estimate the model's parameters for each of many small groups of very similar firms, namely $N = 10$, assuming each firm in the group is exposed to the same permanent shocks. Given the model parameters, the unscented Kalman filter recovers the unobserved state process $x_t \equiv [\log(K_t), \log(L_t)]'$ that determines the likelihood function of the observed $5N$-dimensional data $z_t \equiv [z_{1,1,t}, \ldots, z_{1,5,t}, \ldots, z_{N,1,t}, \ldots, z_{N,5,t}]'$, i.e., earnings, capital, labor, investment and hiring of the N firms in each group and for $t = 1, \ldots, T$:

$$\sum_{t=1}^{T} -\frac{1}{2}\left[5N\log(2\pi) + \log|F_{t|t-1}| + (z_t - \hat{z}_{t|t-1})' F_{t|t-1}^{-1}(z_t - \hat{z}_{t|t-1})\right] \tag{3.18}$$

where $'$ denotes transposition, $z_{t|t-1}$ is the one-step-ahead prediction of z_t based on the filtered state process x_t, and $F_{t|t-1}$ is the error covariance matrix. Maximization of this likelihood function takes about 15 seconds for a panel of $N = 10$ firms observed over $T = 50$ years.

We evaluate the performance of our estimator and compare it to Foster et al. (2016). We carry out a Monte Carlo simulation in which we compare the unscented Kalman filter and the classic Cobb–Douglas log-regression. Appendix 3.C provides the full details. In short, we use the model (3.1) to (3.7) to simulate several panels of data for $N = 10$ firms over $T = 10$ years, mimicking the main empirical work below. For each simulated panel, we obtain two sets of model parameters (i) by maximizing the likelihood function (3.18) and (ii) by running the Cobb–Douglas log-regression using positive earnings data only to recover efficiency e^* and elasticities of capital and labour, γ and β. Simulation results confirm that estimates based on the unscented Kalman filter are by far more accurate than estimates based on the Cobb–Douglas log-regression. The latter suffers from significant bias and inaccuracy, due to capital and labor measurement errors and usage of positive earnings only, and quickly deteriorates when the noise-to-signal ratio increases.

3.3.3. Identification and inference

Estimation of the state space model in (3.11) to (3.17) allows for identification of all three policies. Because the steady-state rates of efficiency e^*, investment i^*, and hiring h^* are constant, they are recovered as the slope parameters of the measurement equations of earnings (3.13), investment (3.16), and hiring (3.17), respectively. Amongst the model's deep parameters, the earnings' elasticities to capital and labor, γ and β, are identified directly off equation (3.13) by the Cobb–Douglas mapping from inputs to earnings. Further, the volatilities of the shocks to the capital and labor stocks are identified off the volatilities of the state variables in the transition equations (3.11) and (3.12). Note finally that the constant terms to the two transition equations are the drift rates μ_K and μ_L. Hence, estimates of i^*, h^*, σ_K and σ_L allow us to recover, rather than having to impute, the depreciation rates δ_K and δ_L.

To illustrate how the model makes inference, we analyze how different combinations of parameter values would imply different characteristics of the data set. Consider Figure 3.2, which shows the sensitivity of two model-implied moments to e^* and σ_K. Both curves in blue represent the combinations of values for the efficiency policy, e^*, and the volatility of shocks to the capital stock, σ_K, that imply the same expected earnings growth rate, $E[CF_{t+1}/CF_t]$, all else constant. These iso-curves are monotonically increasing, implying that any given earnings growth rate, say 2% along the solid blue line, is only attainable with more efficiency if shocks to the capital stock were more volatile. And for a given level of volatility, less efficiency would imply a lower earnings growth rate, e.g., from 2% to 1.9% (dashed blue line).

The black isocurves plot the combinations of e^* and σ_K that imply the same earnings growth variance, $V[CF_{t+1}/CF_t]$, *ceteris paribus*. Keeping e^* constant, e.g., at 0.25, a higher σ_K, e.g., from 0.18 to almost 0.2, implies a higher earnings growth volatility, e.g., from 5.5% (dashed black line) to 6% (solid black line). Moreover, the black isocurves have a slightly negative slope, meaning that with higher e^*, the same earnings growth volatility is obtained with lower σ_K. Further, Figure 3.2 shows that there is a unique combination of e^* and σ_K that produce any given combination of earnings growth rates and volatility. Thus, the model will infer high level of both efficiency and capital shocks volatility from data with relatively high earnings growth rates and volatilities, and vice versa for data with both relatively low earnings growth rates and volatilities.

3.3.4. Data

We use accounting data for publicly listed U.S. firms in Compustat between 1970 and 2019. We exclude financial services firms (SIC codes 6000 to 6999), Utilities (SIC codes 4900 to 4999), Regulated (SIC 8000 to 9999) and firms whose annual asset growth exceeds 500% in any given year. We express all variables in constant 2000 US dollars using the GDP deflator and winsorize them at the 1st and 99th percentiles. Our sample includes 210,637 firm-year observations for 18,026 firms.

We measure operating earnings as EBITDA (oibdp in Compustat) plus investments in intangible assets. Investments in intangibles must be added back to EBITDA because they are treated as an expense rather than a capital investment for accounting purposes. We define intangible investments as R&D expense plus organizational capital and measure the latter using the standard proxy: 30% of SG&A (see, for example, Peters and Taylor 2017b or Crouzet and Eberly 2021).

We define a firm's total capital as the sum of its physical capital (ppegt) and intangible capital. Following the literature (Peters and Taylor, 2017b), we measure a firm's intangible capital as the sum of its knowledge and organizational capital. We proxy knowledge capital investments with R&D and organizational capital investments with SG&A. We apply the perpetual-inventory method to a firm's past R&D and SG&A to measure the respective replacement cost. We compute new capital investments as the sum of physical capital investments (capx) and intangible investments.

Compustat provides the total number of employees (emp) and the total expense in salaries (xlr) but not individual wages. We approximate the number of new hires with the yearly variation in the number of employees, i.e., $\text{emp}_t - \text{emp}_{t-1}$, plus the number of employees leaving the company, predicted using the U.S. Bureau of Labor Statistics' average separation rate for all firms within the same 5 Fama and French (1997) industrial classification. For their salaries, we impute the average salary per firm-year across all firms in the same industry, based on the 5-group classification by Fama and French (1997).

To ensure homogeneity across firms, we normalize each variable by the first availabe observation of book values of total asset (at). Table 3.1 defines each variables and presents its summary statistics.

3.3.5. Firm grouping

We estimate the earnings model in (3.11)–(3.17) for each of *many* small groups of firms. Therefore, we assume that all firms within each group g have the same parameters and, as a result, they choose the same short-term, investment and hiring policies. Fitting the model to relatively small sets of firms allows greater estimation accuracy because the parameter estimates will adjust to the data features specific to each group of firms. Moreover, we obtain a large set of possibly very heterogeneous vectors of estimates of the model's policies and parameters, instead of just very few for the representative firms. Short of firm-by-firm estimation, which is not feasible, estimation by small groups enables the analysis of cross sectional variation in deep parameters and policies.

The fist criterion to classify firms into estimation group is the decade of their IPO. IPO market cyclicality makes firms anticipate or delay their decision to go public, so that firms enter the Compustat sample at different ages or maturities (Ibbotson and Jaffe, 1975). Heterogeneity in the IPO timing decision may imply parameter heterogeneity that we attempt to capture by classifying firms according to their cohort, i.e., decade, of becoming publicly traded. Thus, we split firms into 5 IPO cohorts: 1970s to 2010s.

The other two grouping criteria follow Gryglewicz et al. (2022). These criteria are motivated by the assumption that permanent shocks are common to all firms in the group, while short-term shocks are idiosyncratic. Hence, we group firms based on their 5 Fama and French (1997) industrial classification. We expect firms within the same industrial classification to be exposed to similar short-term volatility (e.g., industry demand uncertainty) and similar permanent shocks (e.g., technology or labor market shocks). Finally, within each cohort and 5 Fama and French (1997) industry, we group firms based on their average annual earnings' growth rate. Indeed, firms with similar permanent shocks will have similar average earnings growth rates in the long-run.

The assumption that permanent shocks are common to all firms in the group is weakened significantly by subsequently (i) sorting by earnings growth rates and (ii) making the groups small. We achieve a high level of granularity with sufficiently high precision in our estimates when all but one of the industry-cohort groups include only ten firms.[5] For $N = 10$, the permanent shock commonality assumption is almost innocuous, and significantly weaker than

[5]Because the number of firms with the same cohort and 5 Fama and French (1997) industry is not generally a multiple of 10, the last group of firms for each cohort-5 Fama and French (1997) industry will include between 10

grouping firms even at the four-digit SIC code level.[6,7] Applying the criteria above, our sample of 18,026 firms is split into 1,801 cohort-5 Fama and French (1997) industry -earnings growth groups.

Table 3.2 shows the decomposition of the total variation of several firm-specific characteristics into the between- and within-group components. Relative to the four-digit SIC or the 17 Fama and French (1997) industry definitions, our classification produces less within-group variation for the ratios of cash flows to initial assets, capital and labor to initial assets, for the age at IPO and firm life, and for key policy variables such as investment and hiring to initial assets. Remarkably, grouping only by long-run similarity in the average cash flow growth rate within each cohort- 5 Fama and French (1997) industry produces similarities across many other dimensions. Table 3.2 shows that our grouping method also produces the most between-group variation for as many firm characteristics relative to the four-digit SIC or the 17 Fama and French (1997) industrial classifications as well as markups estimated following De Loecker et al. (2020b). In a nutshell, our grouping approach produces many small and heterogeneous groups of alike firms.

3.4. Estimation results

Table 3.3 presents estimates of the policies e^*, i^*, and h^*, of the growth rates and volatilities of capital and labor, μ_K, σ_K, μ_L, and σ_L, and of the production function parameters γ, β. Panel A shows the summary statistics assuming the model parameters, and therefore, the policies, remain constant throughout the firms' spell in Compustat. The precision of the estimates is summarized in panel B, as the absolute values of their t-statistics.

All policies exhibit significant heterogeneity across the 1,346 groups of Compustat firms. For example, 95% of firm's investment in tangible and intangible capital ranges between 9% and 34% of total assets. Our estimated average (median) total investment of 20% (18%) for the period of 1970 to 2019 is very close to the average of 21% reported by Peters and Taylor (2017b) for 1975–2011. This result is not surprising because we use the same definition of total investment. However, our estimates are not as volatile, i.e., 8% v. 18%, because they represent steady-state policies and only vary cross-sectionally. The average estimated hiring rate is 15%,

and 19 firms. In the rare cases in which there are fewer than 10 firms in a cohort and 5 Fama and French (1997) industry, we include all firms in one group.

[6]For example, Bates et al. (2009) use the volatility of the average cash flow over all firms in each two-digit SIC code. Similarly, Duchin (2010) uses the correlation between a firm's current cash flow and the median or mean R&D expense over all firms with the same three-digit SIC code.

[7]The assumption that permanent shocks are common to a group of firms encompasses situations in which firms face common technology, labor, regulatory, or consumer preference shocks. An alternative assumption would be to consider that short-term shocks are common to a group of firms while permanent shocks are firm-specific. This would encompass situations in which firms in the same group end up with different productivity growth paths but always face similar temporary disruptions, e.g., weather shocks or common supply-chain disruptions. Because missing values are pervasive in corporate data, it is unclear how to filter out the firm-specific permanent shocks when data are missing. This problem hinders accurate estimation of this alternative model.

with 95% of the group estimates between 6% and 32%. The average of the efficiency estimates is 0.29. This quantity represents the average factor productivity, i.e., the expected earnings per efficient units of labor and capital. Like the other two policies, e^* also varies significantly across firm groups: 95% of the estimates range between 0 and 0.64.

Table 3.3 shows that, on average, the labor growth rate is lower (3%) but is more volatile (69%) than that of the the capital stock (8% and 20%). The fact that estimates of σ_K also exhibit large variation across groups underscores the importance of the joint estimation of policies and the model's deep parameters: as shown in Figure 3.2, correct inference about e^* and i^* depends crucially on controlling for variation in σ_K.[8] The average estimated earnings elasticities are 0.56 for capital and 0.27 for labor. These numbers are direct estimates of the earnings elasticities and the averages are obtained from granular estimates of public firms only. Hence, they are not directly comparable to available estimates based on the measured labor and capital shares using aggregate census data.

3.4.1. Capital accumulation over time

The estimates above are obtained for each group of firms for the whole sample period. Hence, they ought to be interpreted as long-run steady state values. Next, we present and discuss the results from estimating the firm model for each group of firms at different stages of their life as a publicly traded firm: during their IPO decade and then next. We can now compare estimates across groups conditional on the firm's stage in life as a public firm. Thus, differences in parameters and policies are unlikely to be driven by heterogeneity in the duration of firm's Compustat spell.

Figure 3.3 plots the average estimated growth of the capital stock, $\hat{\mu}_K$, for all firms in a given cohort during their IPO decade and the next. We distinguish between firms that exited Compustat due to bankruptcy during the IPO decade (red line) and firms that survived or were acquired in their IPO decade (black line). Estimates for survivors in their second decade are shown in the blue line. Note that each firm has only one estimate per decade, so that time variation in the mean is due to changing composition, i.e., entry or exit of firms within the decade and cohort.

There are some very clear patterns in this figure. First, the average $\hat{\mu}_K$ is fairly constant and precisely estimated for any cohort during the firms' second decade since the IPO. Second, among surviving firms capital growth is significantly slower on average in the second decade relative to the first. Third, capital grows more slowly on average during the first decade for firms that eventually fail relative to those who survive that period, although the difference is not statistically significant for the firms going public in the 1990s. In addition, second decade

[8] These estimates imply an average depreciation rate of capital of 0.10, i.e., $\hat{\delta}_K = \hat{i}^* - \hat{\sigma}_K^2/2 - \hat{\mu}_K = 0.2 - 0.2^2/2 - 0.08 = 0.10$. This estimate coincides with the quarterly depreciation rate of 0.025 calibrated by Clementi and Palazzo (2019).

average growth rates are quite similar for firms going public in the 70s (8%), 90s (9%), or 2000s (7%). Firms who went public during the 80s exhibit a significantly faster average growth (11.5%) in their second decade of public life, i.e., between 1990 and 1999.

We carry out the same analysis for the estimates of the volatility of the growth rate of the capital stock, $\hat{\sigma}_K$, and display the results in Figure 3.4. Firms that failed in their first decade since the IPO have on average a significantly higher $\hat{\sigma}_K$ than the survivors, especially for firms that went public but failed within the 2000s. And for any cohort, the set of survivors is stable throughout the whole second decade since the IPO, resulting in a constant and very precisely estimated average $\hat{\sigma}_K$. We see also that estimates of σ_K increase, from 1% to 2.5% and from 2% to 4%, for firms that went public in the 70s and 80s. However, for survivors of the 90s and 2000s IPOs, we cannot reject that the average $\hat{\sigma}_K$ changes between the first and second decades.

Not having imposed any restriction *a priori*, it is remarkable that the average of the estimates of σ_K change little over two decades, and not at all for firms that went public since 1990. Moreover, this result implies that the reason for the drop in the average growth rate of the capital stock from the IPO decade to the next, a pattern that pervades all cohorts, cannot be solely that investment became more risky. Indeed, recall that μ_K along the steady-state path is given by $i^* - \delta_K - \sigma_K^2/2$, so that σ_K impacts the average growth rate negatively, both directly and indirectly through its equilibrium effect on investment.[9] And yet the most pronounced drop in the average $\hat{\mu}_K$ is for the 90s and 2000s cohorts, whose average $\hat{\sigma}_K$ remained constant from their IPO decade to the next. Corroborating this finding, Figure 3.5 shows that the drop in average $\hat{\mu}_K$ coincides with reductions in the investment rate, i^*, and again especially in the decades during which average $\hat{\sigma}_K$ remained constant.

The decrease in average μ_K or i^* as firms survive their IPO decade into the next cannot be easily reconciled either with the change in the average estimated earnings elasticity of capital, $\hat{\gamma}$. Figure 3.6 shows that the average $\hat{\gamma}$ *increases* for all but the 2000s cohort. That is, for firms going public in the 70s, 80s and 90s capital accumulation slowed down on average despite becoming marginally more productive from the IPO decade to the next. If changes in γ or σ_K cannot fully account for slower investment as firms mature, then what else could be the reason? To answer this question, we now look into what happened to investment jointly with the provision of efficiency during the same transition.

3.4.2. Investment and efficiency over time

We compare efficiency and investment policies in Figure 3.7, which plots the time series of the average of the ratio of optimal efficiency to optimal investment, e^*/i^*, distinguishing between the firms that failed during the IPO decade (red line), and the firms that survived it (black line, for the IPO decade, and blue line for the next decade).

[9] Appendix 3.A.1 shows that $\partial i^*/\partial \sigma_K^2 < 0$.

Figure 3.7 shows that, amongst survivors, the average e^*/i^* ratio increased significantly from the IPO decade to the next regardless of the cohort. The later the cohort, the larger the increase: For firms that went public in the 2000s, the average ratio almost doubles, from 1.5 to 2.75. Except for the 70s cohort, the e^*/i^* ratio is also significantly higher for firms that survived rather than failed during the decade of the IPO. Figure 3.8 explores whether the difference between the average e^*/i^* ratios of firms that survived and firms that failed during the IPO decade can be explained by age differences at the time of the IPO: It presents the distributions of the e^*/i^* ratio in the IPO decade conditional on the firm's age when going public. We also distinguish between firms that failed during this decade (red), that did not fail but were acquired and therefore de-listed (white), or survived (blue). Figure 3.8 shows that, conditional on a firm's fate after the IPO decade, the average e^*/i^* ratio increases with the firm's age at the time of IPO. However, these differences are relatively small compared to the differences in e^*/i^* between failed and surviving firms within each age group.

We make two observations that summarize the findings so far. First, the model estimates suggest that firms prioritize efficiency over growth as they mature by increasing the intensity of efficiency relative to capital investment over time. Second, that controlling for age, firms going public with higher efficiency to investment ratios are more likely to survive and mature. In short, a firm's prevalence is related to its e^* and i^* policies early on.

3.4.3. Investment and efficiency across industries

Figure 3.9 displays the distributions of the e^*/i^* ratio during the IPO decade and the next for the four major industry groups in the 5-industry Fama and French (1997) classification: Consumer Goods, Manufacturing, Technology and Healthcare. Table 3.4 presents additional statistics of these policies and parameter estimates conditional on the industry and whether the firms survived or failed during the IPO decade (Panel A) as well as their changes from the IPO decade to the next (Panel B). Panel A shows that firms in the Healthcare sector are on average the youngest to go public. In the second decade after the IPO, the average firm in Healthcare has the lowest average $\hat{e}^*/\hat{i}^*$. The highest average ratio is for Manufacturing, which also has the lowest average optimal investment rate during the second decade after the IPO: 15%.

Figure 3.9 shows that the $\hat{e}^*/\hat{i}^*$ average ratio increases from the firm's IPO decade to the next in all four major industry groups. The ratio goes up by 0.41 (standard error 0.17) in the Healthcare industry, where the change is most pronounced (Panel B of Table 3.4), but it is also economically and statistically significant for the Consumer Goods industry, 0.41 (0.14), Manufacturing, 0.29 (0.17), and the Technology sector, 0.37 (0.12). For all industries, the $\hat{e}^*/\hat{i}^*$ ratios are more dispersed in the second decade, as the distribution skews more to the right.

Table 3.5 describes in detail the changes in the $\hat{e}^*/\hat{i}^*$ ratio over both decades by the firm's industry and cohort. This table reports the slope coefficients from the regression of the group-specific change in the $\hat{e}^*/\hat{i}^*$ ratio from the IPO decade to the next on a constant, binary indicators (0 or 1) for the decade of IPO of the firms in each group ($1\{\text{IPO in DD}\}$ for DD = 80s, 90s or 00s), and the products between these cohort dummies and the changes from one decade to the next in the capital stock volatility, $\Delta\hat{\sigma}_K$, and the elasticity of earnings with respect to capital, $\Delta\hat{\gamma}$. As additional controls, the regressions include the labor stock volatility and the labor elasticity of earnings (unreported). We see in Table 3.5 that none of the coefficients for the cohort dummies in any industry are negative and statistically significantly different from zero. This result confirms that the average $\hat{e}^*/\hat{i}^*$ ratio increases from the IPO decade to the next for all cohorts and all four major industry groups. There are only three cases in which the increase in efficiency relative to investment occurs simultaneously with an increase in the capital stock volatility: for the 80s and 2000s cohorts in the Consumer Goods industry and for the 70s cohorts in Healthcare. For all other cases, the increased focus on efficiency relative to growth is uncorrelated with the change in $\hat{\sigma}_K$ or, as for Healthcare since the 2000, occurs despite a decrease in $\hat{\sigma}_K$.

If not the case on average, the coefficients in Table 3.5 suggest that the increased focus on efficiency from the first decade as a public firm to the next is associated with lower capital productivity for some industries and cohorts. Some of the coefficients of the interactions between cohort dummies and $\Delta\hat{\gamma}$, namely for 90s entrants in all but the Healthcare industry, or for all 70s entrants not in Manufacturing, are indeed negative and significantly different from zero. To summarize, our model estimates show an increased focus in efficiency relative to growth that is partially driven by a decreasing earnings elasticity of capital for some industries and cohorts but not often by a higher capital stock volatility. However, firms across all industries and cohorts exert relatively more efficiency than investment going from the decade of IPO to the next over and above the changes in these fundamentals. In other words, the increased focus of efficiency over growth appears to come naturally with maturity.

3.5. Understanding growth versus efficiency choices

Short-term effort and investment policies not only change over time but also vary significantly within each decade and cohort. We ask next what explains the cross-sectional variation and what are the long-term consequences of these choices.

3.5.1. Determinants of efficiency and investment policies

Table 3.6 explores the relation between short-term or investment policies and the deep parameters of the model. It shows the coefficients of firm-level cross-sectional regressions of $\hat{e}^*$, $\hat{i}^*$, or the ratio $\hat{e}^*/\hat{i}^*$ on estimates of the earnings elasticities of capital and labor, and the volatilities of the shocks to the capital and labor stocks. Controls include the logarithm of the age, in years, of the firm at the time of the IPO and Fama and French (1997) 5-industry fixed effects. The estimates in the second row show that higher values of $\hat{\sigma}_K$ are significantly correlated with lower investment rates only during the IPO decade for firms that eventually survived it. For these firms, a higher capital stock volatility is also associated, on average, with lower efficiency. However, we cannot reject that the correlation between σ_K and the s/i ratio is different from zero. For these same firms, differences in the capital stock volatility are no longer related to either e nor i in the next decade. Instead, and similar to the time series analysis, differences in e^*, i^* or their ratio are better explained by heterogeneity in the estimated capital elasticity of earnings, $\hat{\gamma}$: the third row of Table 3.6 shows negative and statistically significant coefficients of e^* or e^*/i^* on γ in either decade for firms that survived the IPO decade. That is, amongst the survivors, firms with higher capital productivity are on average more focused on growth as opposed to efficiency relative to equally aged firms during their IPO decade or beyond.

The coefficients on the cohort fixed effects reveal that the largest e^*/i^* ratios in the decade after the IPO, over and above differences explained by the estimated fundamentals, are for the firms that went public in the 80s or 90s. Finally, the cross-sectional analysis confirm that heterogeneity in the firm's age at the time of the IPO is strongly negatively correlated with investment and positively correlated with efficiency, for any firm but only in the decade of IPO and not afterwards. To summarize, the cross-sectional heterogeneity in e^* and i^* policies amongst firms that survive beyond their IPO decade is partially explained by heterogeneity in capital productivity early on. The only common factor explaining differences in policies for both failed firms and survivors is age, with older firms more focused on efficiency than growth, i.e., higher e^*/i^* ratios.

3.5.2. Policies and outcomes for young firms

Table 3.7 explores the relation between different product market outcomes and firm policies. It shows the coefficients from the regressions of the estimates of the marginal cost markups in De Loecker et al. (2020b) (Panel A) or of the logarithm of annual sales (Panel B) on the efficiency and investment policies during the IPO decade, controlling for the age of the firm at its IPO and cohort (decade of IPO) and industry (5-industry Fama and French 1997) fixed effects. We distinguish between firms that failed or survived the IPO decade. To facilitate the comparison between groups, we report the economic significance, in brackets, as the change in the dependent variable relative to its sample mean given a one standard deviation change in each policy.

The coefficient estimates in the first column of Table 3.7 show that the surviving firms with the highest efficiency are, on average, also those with the highest markups and annual sales. High investment firms tend to also have higher markups but lower sales, on average. Similar results are obtained for firms that failed. After controlling for the firm's age at IPO (columns 4 to 6), investment is no longer related to the markups of either surviving or failed firms during the IPO decade. The variation in investment appears to be subsumed by the variation in the firm's age at its IPO in that firms going public earlier invest more on average and have higher markups during the IPO decade. However, differences in efficiency provision are positively correlated with differences in the markup, and the relation is statistically and economically significant: one standard deviation differences in e^* are associated with 8.2% and 15.2% differences (average of 10.5%) in the average price-cost markup for survivors and failed firms. The other consistent result amongst either failed firms or survivors, after controlling for age at IPO is that high investment firms have lower sales. However, the investment differences amongst survivors only are economically more meaningful than amongst failed firms: a one standard deviation increase in investment implies 50.5% lower sales for the former but 29.8% lower sales for the latter.

We summarize our analysis of the IPO decade as follows. On average, older firms are larger and invest less than younger firms of the same cohort and industry. As they exert more efficiency, they are already more focused on efficiency as opposed to growth and can charge higher markups.

3.5.3. Policies and outcomes for mature firms

We repeat the previous analysis but this time for the decade following the IPO decade. In addition to the markup and the logarithm of annual sales, we also analyze the growth in average sales from the first decade to the next. Results are presented in Table 3.8. Qualitatively, the results are very similar for this decade than the previous. Namely, that firms that went public older, which exhibit higher efficiency but lower investment, are larger and have higher markups on average.

Quantitatively, the relation between efficiency policy and the markup or sales is bigger: a one standard deviation increase in e^* is associated with a 14.2% increase in the average markup and 33.1% more sales. In addition, firms with the highest efficiency in the second decade are those whose sales grew the most from the IPO decade to the next. In short, the increasing focus on efficiency over growth by larger, older firms appears more pronounced in the period following the IPO decade. But if the evidence so far shows that the choice between growth and efficiency depends to a large extent on the firm's age and maturity, and to a lesser extent on deep parameters of the production function, there still exists significant heterogeneity in e^* and i^* over and above such fundamentals. To understand this additional heterogeneity, we ask what is the impact on long-term product market outcomes of policy choices made during the IPO decade.

3.5.4. Long-term effects of policies

We test whether policy choices made in the IPO decade predict product market outcomes afterwards. We look into the markups, the logarithm of sales and the sales growth over three different horizons: years 0 to 5, years 6 to 10 and years 11 to 15 after the IPO decade. Table 3.9 reports the coefficient estimates from these predictive regressions. The first column shows that higher efficiency predicts higher markups, higher sales and higher sales growth in the five-year period following the IPO decade: For each outcome, the coefficients of e^* are positive and statistically different from zero. Higher investment also predicts higher markups and sales growth, if lower sales. Column 1 also shows that the economic effect, shown in brackets, of IPO decade investment on the markup in the subsequent five-year period is not as large as the effect of efficiency. But caution is warranted in interpreting these results: the estimates of these predictive regressions have a sample selection bias in that some firms fail and are de-listed during the IPO decade. And Figure 3.7 already shows that the firms least likely to survive past the IPO decade are those with the lowest e^*/i^* ratios. Hence, OLS estimates are based on samples that are biased towards firms with low investment rates, compromising our inference about the long-run effects of early investment by the average public firm.

We address the sample selection problem due to firm de-listing during the IPO decade using the Heckman (1979) correction, which we implement by maximum likelihood. We model the selection equation as the following probabilistic model:

$$\begin{aligned}\text{Prob}[\text{Firm}\, f \text{ survives IPO decade}] = &\underset{(0.09)}{1.06} + \underset{(0.10)}{1.08} e^*_f - \underset{(0.27)}{3.05} i^*_f - \underset{(0.25)}{1.95} \sigma_{K,f} - \underset{(0.27)}{0.37} \mu_{K,f} \\ &+ \underset{(0.01)}{0.02} \text{Prob}[\text{U.S. goes into Recession}] \end{aligned} \tag{3.19}$$

where the dependent variable is the probability that the firm f survives its IPO decade. As determinants of the firm's survival we include the firm's efficiency and investment policies in the IPO decade. As instruments for selection we include the firm-specific values of the deep parameters $\sigma_{K,f}$ and $\mu_{K,f}$. As an additional instrument capturing the state of the economy we include the probability that the U.S. economy enters into a recession in the next month, estimated by the Federal Reserve Bank of St. Louis, and recorded at the month of the firm's IPO.

The signs of the estimates of equation (3.19) are as expected and are consistent with our time series analysis: Firms with higher efficiency but lower investment, i.e., relatively more focused on efficiency than growth, have a higher chance of surviving their IPO decade. Additionally, firms with more volatile shocks to the value of their capital stock or that went public when a recession was more likely to follow are less likely to survive. Column 2 (labeled 'Heckman') shows the coefficients of the predictive regressions after correcting the sample selection bias. Across all panels and for the 0 to 5 and 6 to 10 horizons, the results are the same, qualitatively. Quantitatively, there are noteworthy differences.

Correcting for sample selection bias, the economic effect of early efficiency on the future markup becomes much smaller, decreasing by a factor of 11 (Panel A). Moreover, the economic effect of early investment on the future markup remains constant or becomes even stronger following the Heckman (1979) correction. This effect is about eight times that of efficiency in the 0 to 5-year period following the IPO decade, and almost 1.5 times or 3.4 times larger in the

6 to 10- or 11 to 15-year periods following the IPO decades. These results confirm that it is the high investment firms that drop out, and that the post-IPO decade sample includes firms that invested less early on but survived. Further, the results also show that firms focused on growth early on expect higher markups than those focused on efficiency conditional on surviving into the next decade. On the downside, it appears these firms were relatively more vulnerable to negative shocks, and therefore, more likely to fail during their IPO decade. In a nutshell, firms face the following trade-off: high investment implies higher long-term markups but a higher risk of early failure.

3.5.5. External validity: the Great Financial Crisis of 2008

If our interpretation that growth firms aim for higher markups in the long run while risking failure shortly after going public is correct, our estimates of e^* and i^* should be able to predict survival and failure following an identifiable shock common to all firms. As external validation of our policy estimates and of our interpretation, we check whether high e^*/i^* firms were more likely to survive the Great Financial Crisis of 2008 (GFC).

To implement this validation we estimate our model for all groups of firms the decade before and the decade after the GFC: from 1996 to 2006 and 2010 to 2019. Figure 3.10 shows the average e^*/i^* ratio each year leading to and following the GFC, in blue for surviving firms and in red for firms that failed during the GFC. Validating our interpretation, the figure shows that the average survivor of the GFC had significantly higher levels of efficiency relative to the investment rate than the average failed firm.

3.6. Asset pricing implications

Our framework provides granular estimates of Compustat firms' deep parameters and policies that directly impact their states of profitability and their investment. Hence, our estimates should capture the heterogeneity in a panel of firms that determines equity returns via the supply side. Therefore, one natural way to validate our exercise consists of testing whether our estimates of efficiency, investment and the earnings elasticity to capital help explain the cross-section of returns as predicted by the Investment CAPM.

In the Investment CAPM, each firm's loading on the aggregate investment and profitability factors, i.e., the investment and profitability betas, are functions of the firm's own state of investment and profitability (Hou et al., 2015; Liu et al., 2015; Zhang, 2017). The reason is that profitability and investment are jointly determined with the firm's discount rate: high profitability but low investment imply high discount rates because, in the steady state equilibrium, low investment can only occur simultaneously with high profitability if the discount rate is high, so as to lower the NPV of investment opportunities.

Our method provides direct estimates of the firm's optimal investment. Also, in our model, profitability is monotonically increasing in e^* and γ, given that profitability equals $c\gamma K^{\gamma-1}L^{\beta}$ and that $\partial c/\partial e^* > 0$ (see Appendix 3.A.1 for the proof). Hence, our data set produces different combinations of investment and profitability that can be compared to actual excess returns in the data. In particular, as high profitability firms expect higher stock returns, it follows that our estimates of efficiency or of the earnings elasticity to capital should be strongly positively correlated with the cross section of profitability betas, i.e., with the loading on the expected positive return of the profitability (return on equity – ROE) factor. Conversely, as high investment firms expected lower excess returns, it follows that our estimates of the investment rate should be strongly negatively correlated with the investment factor betas, that is, the loading on the expected positive return of the investment factor.

We follow the standard practice to implement these tests. We form portfolios of stocks based on our grouping of firms (Section 3.3.5) and consider the monthly returns of these portfolios throughout our sample period, from 1971 to 2019. We compute the betas for investment, profitability and size, i.e., $\beta_{I/A}$, β_{ROE}, β_{ME}, from the time series regressions of the portfolio returns on the investment, profitability and size factors calculated by Hou et al. (2015), controlling for market returns.[10] Then, we regress the cross section of each estimated beta on the cross-sectional estimates of e^*, i^* and γ, controlling for cohort and industry fixed effects.

Table 3.10 summarizes the regression results. Three findings there are worth mentioning. First, the investment rate impacts negatively the investment beta, $\beta_{I/A}$. Second, the profitability beta, β_{ROE}, loads positively on efficiency. Third, the profitability beta also correlates positively with the elasticity of earnings to capital. The coefficients supporting these results are different from zero with 95% or 99% confidence. All of these findings are in line with the Investment CAPM theory.

As discussed above, our estimates of efficiency and investment policies reflect the firms' choices between growth and efficiency over their life cycle. Young firms focus on growth, investing relatively more and exerting relatively less efficiency than mature firms. The asset pricing implication is that young firms are less exposed to both the investment and profitability factors. Mature firms are more efficient and productive, as captured by higher e^* and γ, and therefore have a higher exposure to the profitability factor. Table 3.10 also analyzes the exposure to the size factor. The third column shows that the size beta, β_{ME}, loads negatively on efficiency and positively on investment. As we showed previously, large firms are relatively more focused on efficiency and smaller firms on growth. Therefore, our results suggest that large firms tend to have a low exposure to the size factor (Hou et al., 2015) because large firms tend to have high e^* but low i^*.

In sum, our estimates of efficiency and investment, which appear to capture the stage in the

[10] The investment, profitability, size, and market factors are available at `https://global-q.org/factors.html`.

life cycle of a firm, suggest that the choice between growth versus efficiency plays a role in explaining the cross section of stock returns from the supply side, not only via their exposure to the investment and profitability factors, but also to the size factor.

3.7. Conclusion

We can observe how much a firm invests in tangible or intangible capital and labor but not how much effort it exerts in the short-term to make production more efficient. This paper develops a framework to model the firm's decision between growing or being efficient and to estimate the unobservable level of efficiency. Representing the majority of Compustat firms since the 1970s, and with a high level of granularity, the estimates produce the robust finding that young firms focus on growth and mature firms prioritize efficiency. This result pervades all industries and firm cohorts.

This paper also identifies the consequences of different efficiency and investment policies by firms of the same age and in the same industry: firms focused on growth when young have the highest markups in the long-term, whereas firms focused on efficiency have higher chances of surviving in the long-term. Why similar firms choose growth versus efficiency differently can be partially explained by some observable fundamentals, but a full explanation ought to be given in future research.

As a tool to measure unobservable short-term policy, this framework can be viewed as a stepping stone towards quantifying the impact of managerial biases, such as short-termism, on the choice between efficiency and growth. Estimation of this model, augmented with agency conflicts, is a natural extension we undertake in ongoing research.

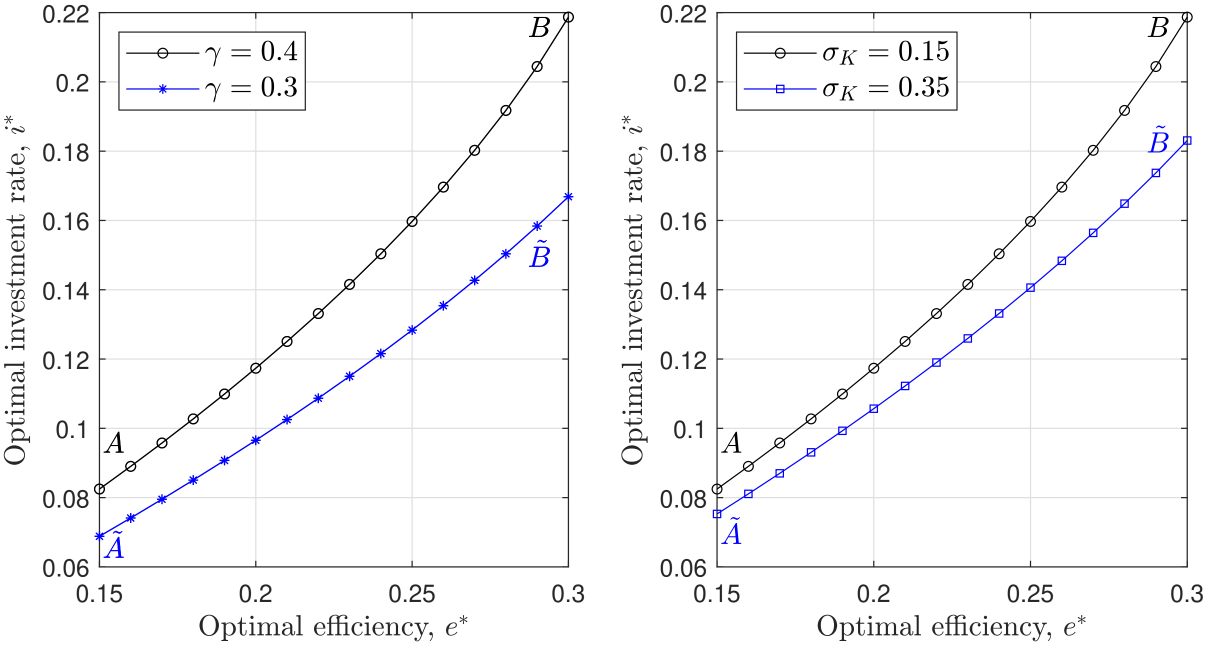

Fig. 3.1 Model comparative statics. The figure plots the combinations of optimal investment rate, i^*, and optimal efficiency $e^* = 1/\lambda_e$, as efficiency adjustment costs, λ_e, vary between 3.33 (points A and $\tilde{A}$) and 6.66 (points B and $\tilde{B}$). For the black lines in either panel, all other parameters are set to $\lambda_K = 2.5$, $\lambda_L = 4.5$, $\delta_K = 0.2$, $\delta_L = 0.1$, $\sigma_K = 0.15$, $\sigma_L = 0.3$, $\gamma = 0.4$, $\beta = 0.3$, $r = 0.045$. For the blues lines, $\gamma = 0.3$ on the left panel and $\sigma_K = 0.35$ on the right panel, while all other parameters remain constant.

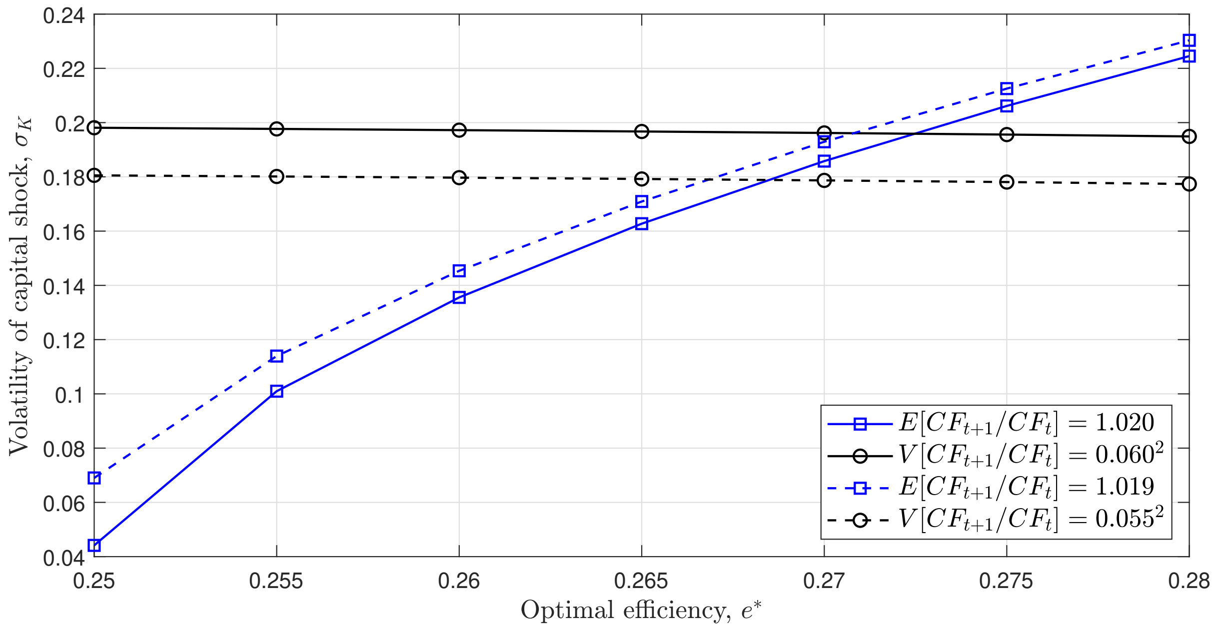

Fig. 3.2 Sensitivity of model-implied moments to e^* and σ_K. The figure plots two types of iso-curves. Each curve in blue represents the combinations of values for the efficiency policy, e^*, and the volatility of capital shocks, σ_K, that imply a given expected earnings growth rate, $E[CF_{t+1}/CF_t] = 1.020$ or 1.019, all else equal. For the blue solid line, the earnings growth rate is 2%; for the blue dashed line, it is 1.9%. Each curve in black represents the combinations of e^* and σ_K that imply a given earnings growth variance, $V[CF_{t+1}/CF_t] = 0.060^2$ or 0.055^2, all else equal; 6% for the black solid line and 5.5% for the black dashed line.

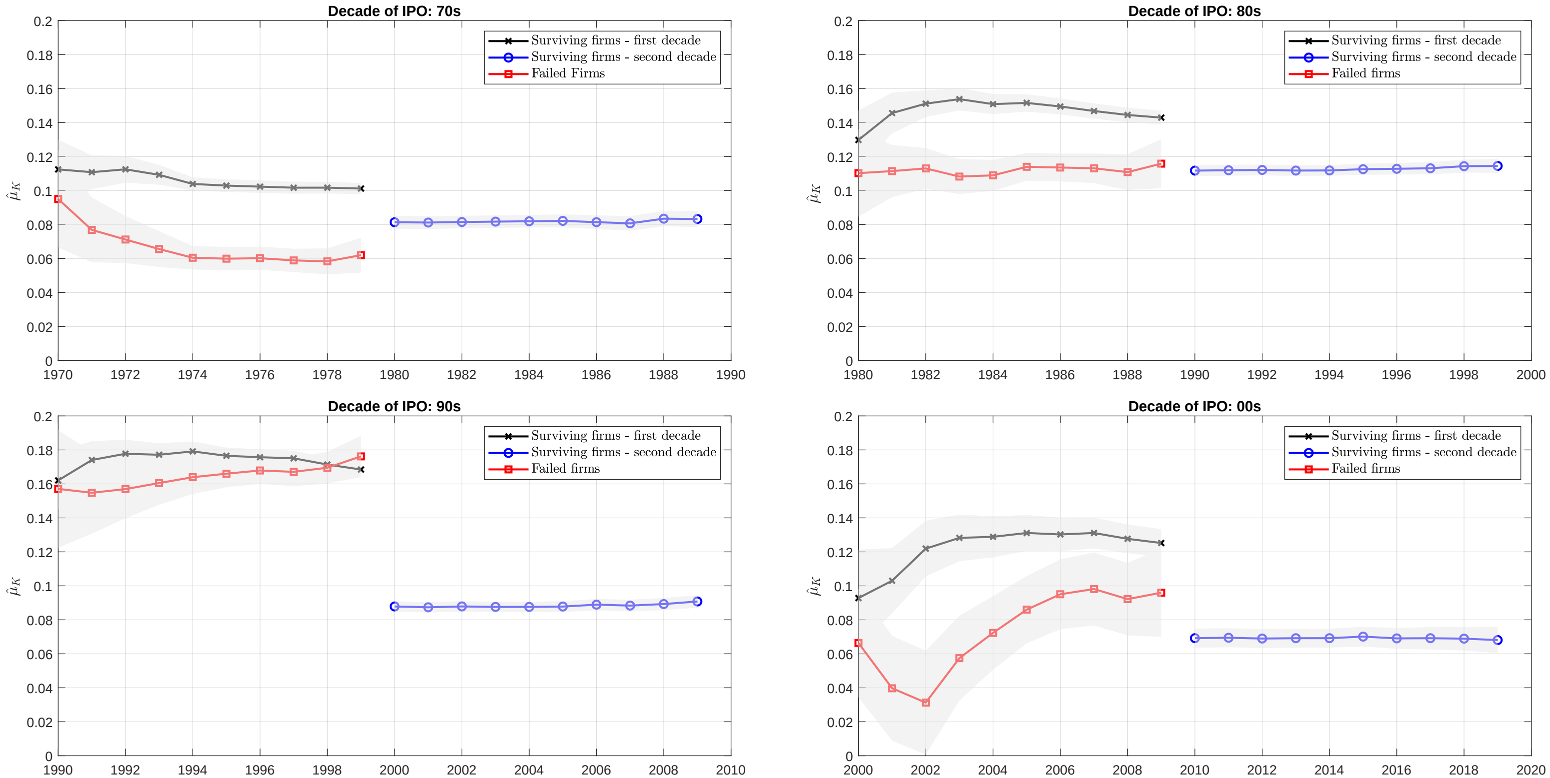

Fig. 3.3 **The growth rate of the capital stock over time.** This figure plots the time series of the average estimated growth rate of the capital stock, $\hat{\mu}_K$, during the decade in which a firm went public and during the subsequent decade. For the first decade, the model is estimated separately for firms that failed and were de-listed (red line) or survived into the next decade (black line). The sample includes all Compustat firms from 1971 to 2019 with at least (not necessarily consecutive) 10 years of annual data. The firm model is estimated on 1,346 groups of firms. The shaded area represents the 95% empirical confidence interval for the mean.

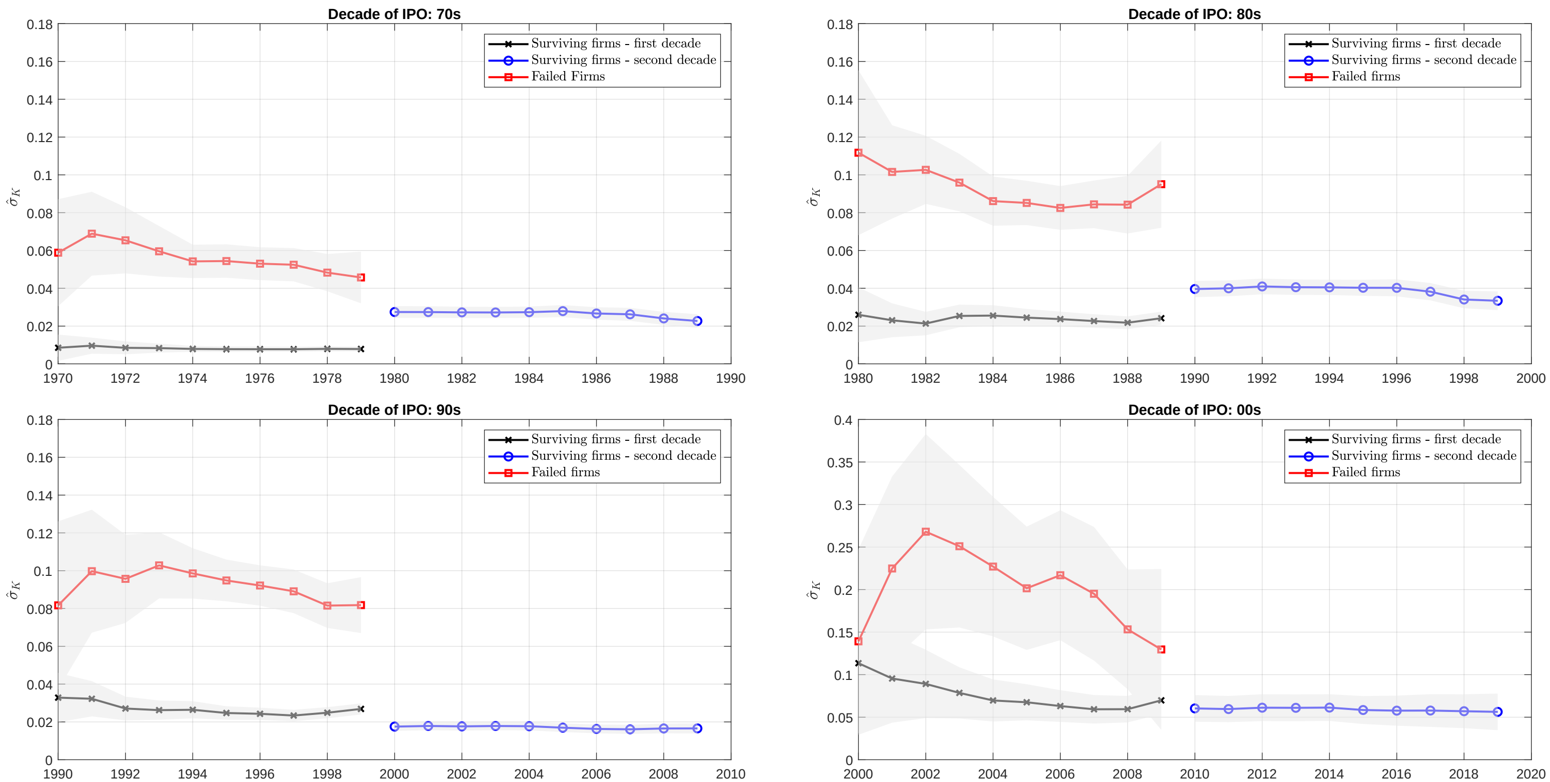

Fig. 3.4 The volatility of the capital stock over time. This figure plots the time series of the average estimated volatility of the capital stock growth rate, $\hat{\sigma}_K$, during the decade in which a firm went public and during the subsequent decade. For the first decade, the model is estimated separately for firms that failed and were de-listed (red line) or survived into the next decade (black line). The sample includes all Compustat firms from 1971 to 2019 with at least (not necessarily consecutive) 10 years of annual data. The firm model is estimated on 1,346 groups of firms. The shaded area represents the 95% empirical confidence interval for the mean.

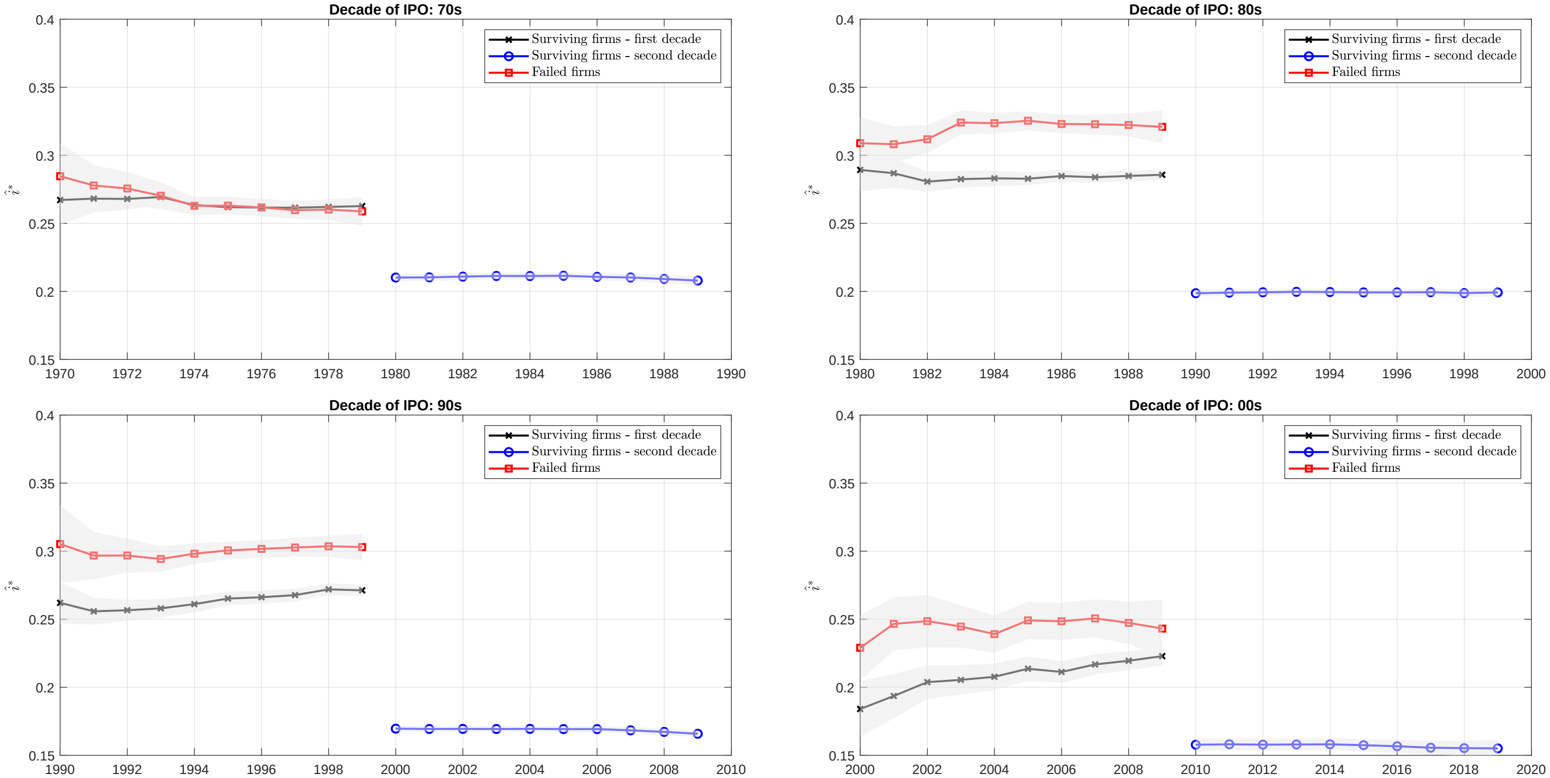

Fig. 3.5 The investment rate over time. This figure plots the time series of the average estimated investment rate, $\hat{\imath}^*$, during the decade in which a firm went public and during the subsequent decade. For the first decade, the model is estimated separately for firms that failed and were de-listed (red line) or survived into the next decade (black line). The sample includes all Compustat firms from 1971 to 2019 with at least (not necessarily consecutive) 10 years of annual data. The firm model is estimated on 1,346 groups of firms. The shaded area represents the 95% empirical confidence interval for the mean.

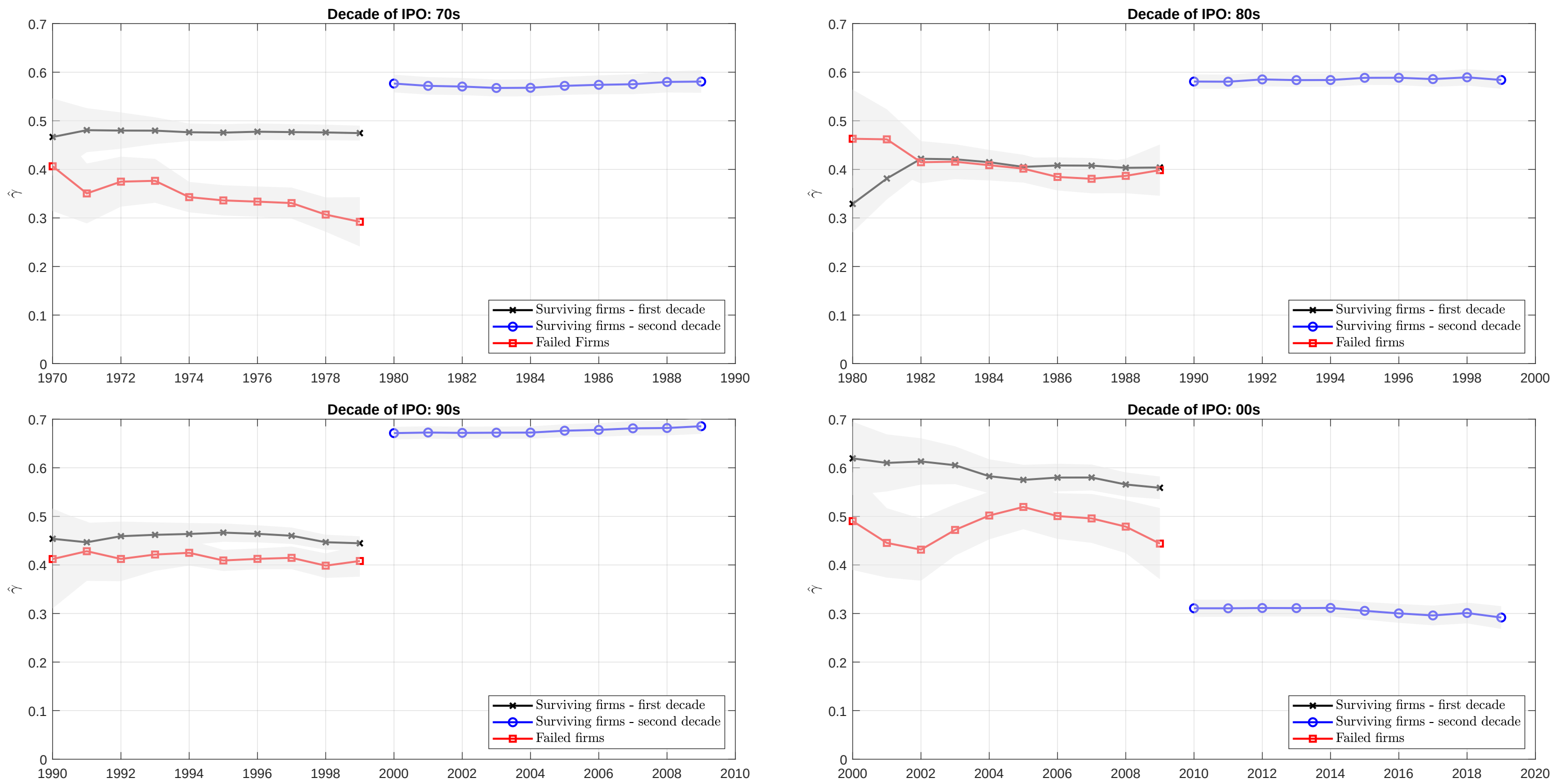

Fig. 3.6 The capital elasticity of earnings over time. The figure plots the time series of the average estimated elasticity of earnings with respect to capital, γ, during the decade in which a firm went public and during the subsequent decade. For the first decade, the model is estimated separately for firms that failed and were de-listed (red line) or survived into the next decade (black line). The sample includes all Compustat firms from 1971 to 2019 with at least (not necessarily consecutive) 10 years of annual data. The firm model is estimated on 1,346 groups of firms. The shaded area represents the 95% empirical confidence interval for the mean.

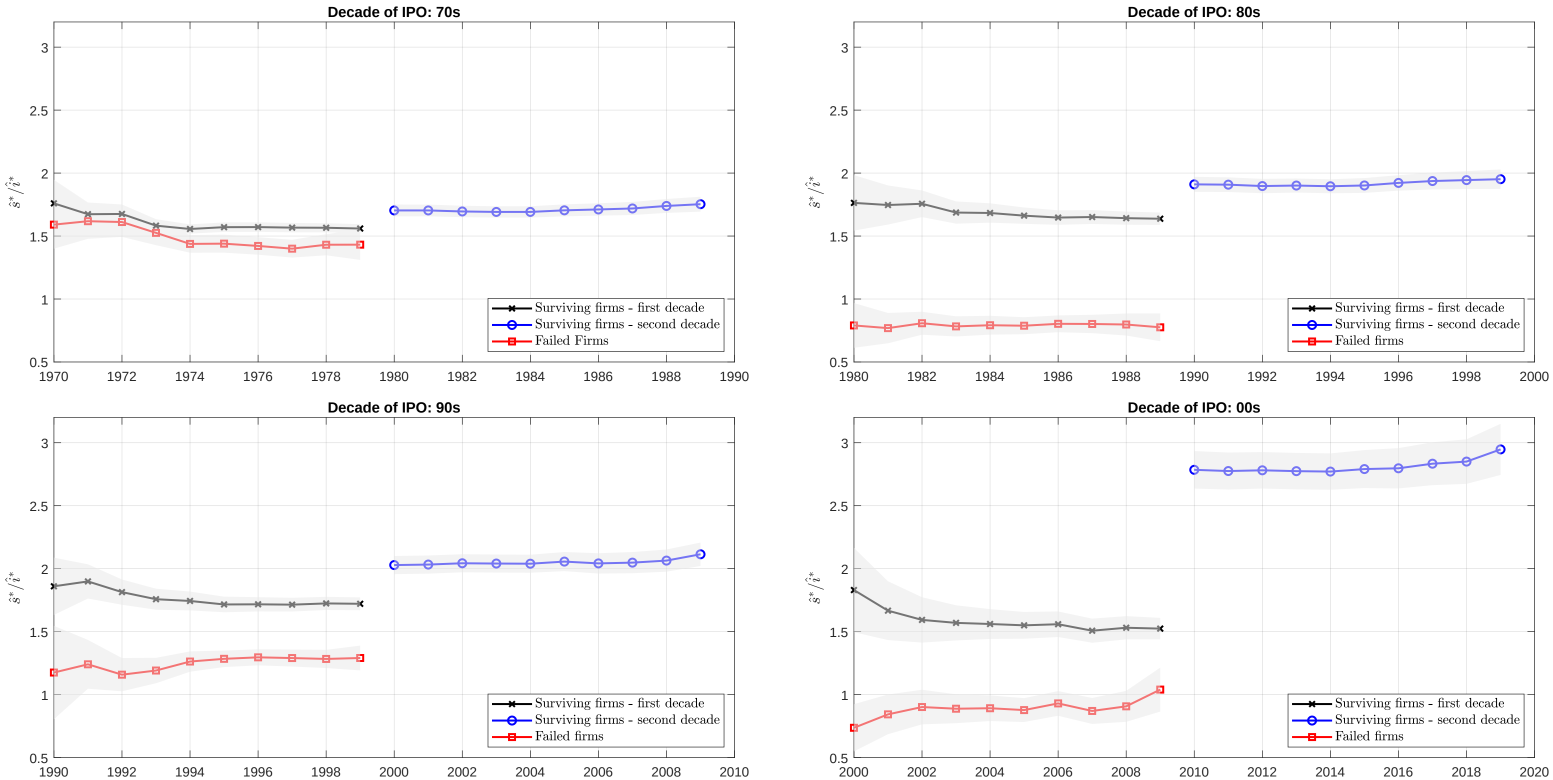

Fig. 3.7 **The efficiency-to-investment ratio over time.** The figure plots the time series of the average estimated efficiency-to-investment ratio, $\hat{e}^*/\hat{i}^*$, during the decade in which a firm went public and during the subsequent decade. For the first decade, the model is estimated separately for firms that failed and were de-listed (red line) or survived into the next decade (black line). The sample includes all Compustat firms from 1971 to 2019 with at least (not necessarily consecutive) 10 years of annual data. The firm model is estimated on 1,346 groups of firms. The shaded area represents the 95% empirical confidence interval for the mean.

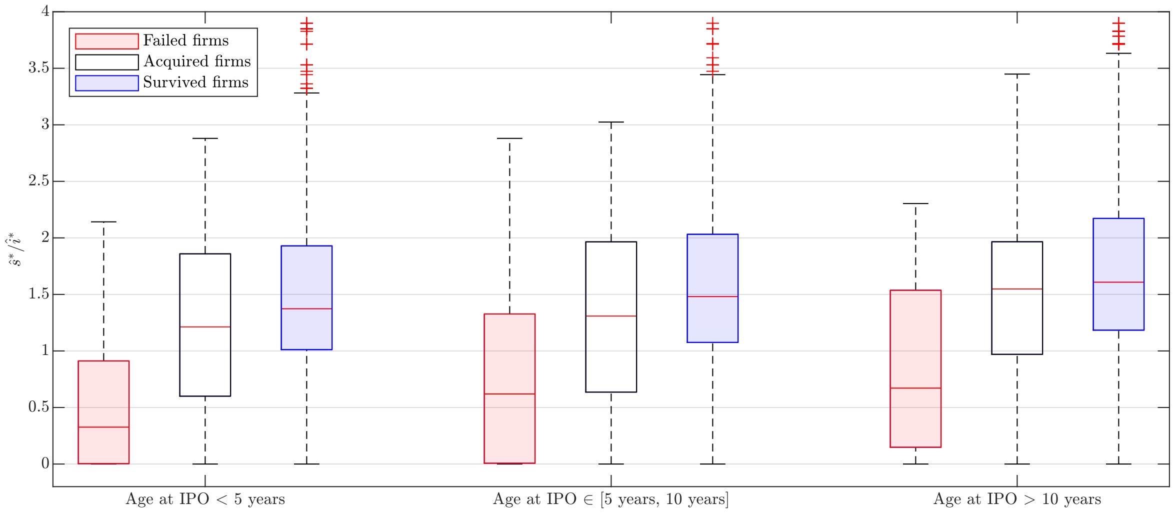

Fig. 3.8 **Firm age and efficiency-to-investment ratio during the IPO decade.** The figure shows the distribution of the estimated ratio of efficiency to investment, $\hat{e}^*/\hat{i}^*$, during the decade in which the firm went public, conditional on the age of the firm at the IPO and whether the firm failed, was acquired or survived the decade. The sample includes all Compustat firms from 1971 to 2019 with at least (not necessarily consecutive) 10 years of annual data. The firm model is estimated on 1,346 groups of firms.

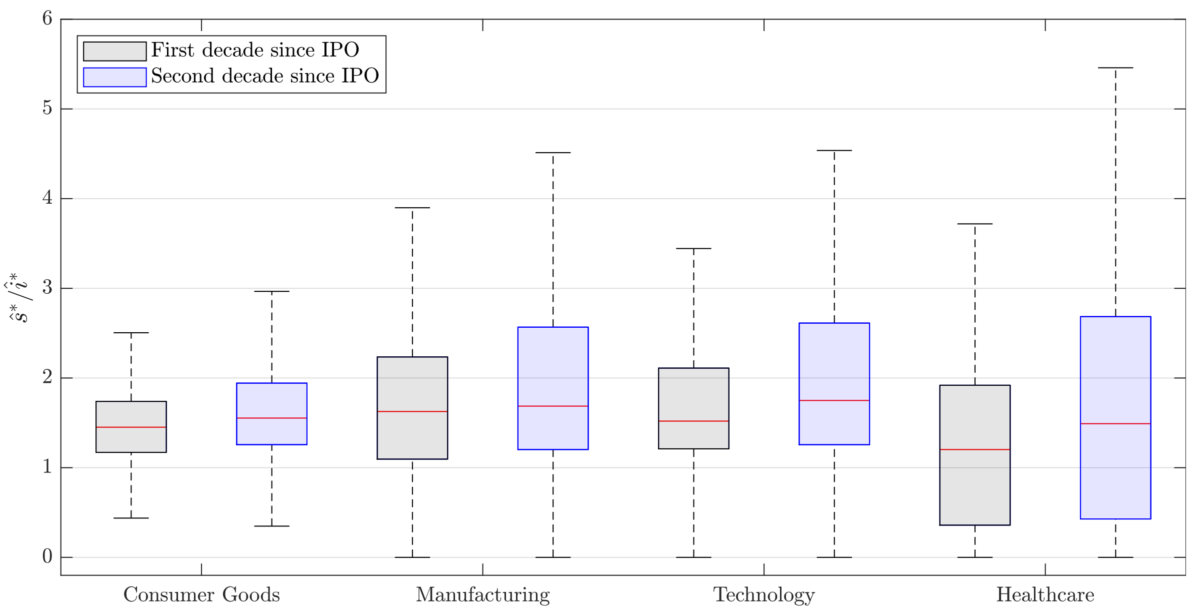

Fig. 3.9 **The efficiency-to-investment ratio across industries.** The figure shows the distribution of the estimated ratio of efficiency to investment, $\hat{e}^*/\hat{i}^*$, during the decade in which the firm went public and during the subsequent decade for the four major groups in the 5-industry classification by Fama and French (1997). The sample includes all Compustat firms from 1971 to 2019 with at least (not necessarily consecutive) 10 years of annual data. The firm model is estimated on 1,346 groups of firms.

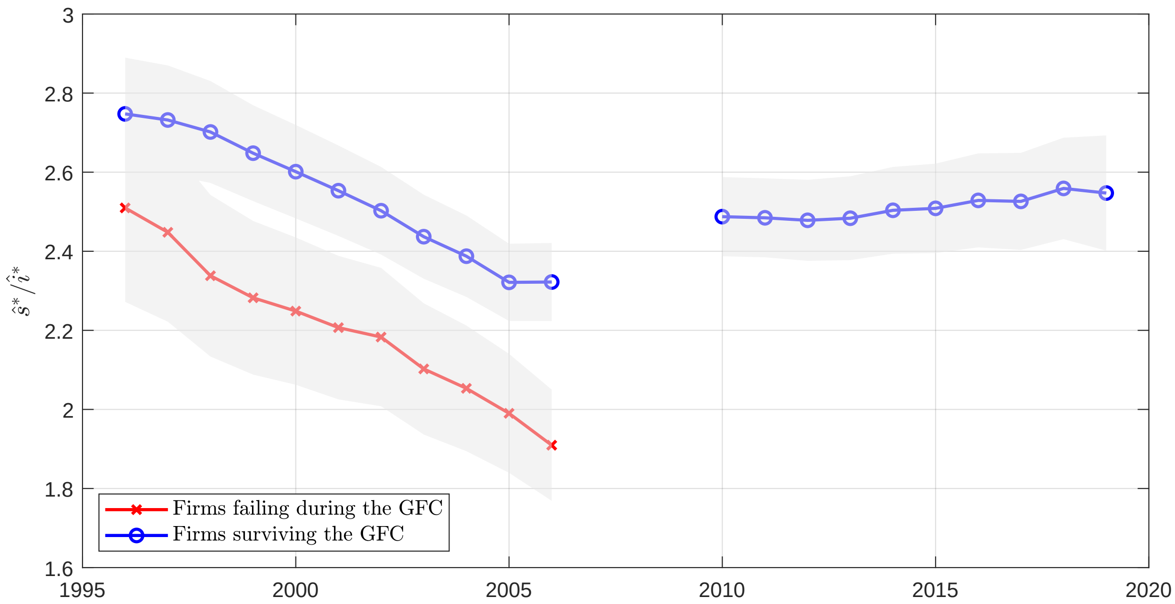

Fig. 3.10 **The efficiency-to-investment ratio around the Great Financial Crisis.** This figure plots the time series of the average estimated efficiency-to-investment ratio, $\hat{e}^*/\hat{i}^*$, for the ten-year periods before and after the Great Financial Crisis of 2007 to 2009. For the 1996–2006 period, the model is estimated separately for firms that failed and were de-listed (red line) or survived into the 2010-2019 period (black line). The sample includes all Compustat firms from 1996 to 2019 with at least (not necessarily consecutive) 10 years of annual data. The firm model is estimated on 790 groups of firms. The shaded area represents the 95% empirical confidence interval for the mean.

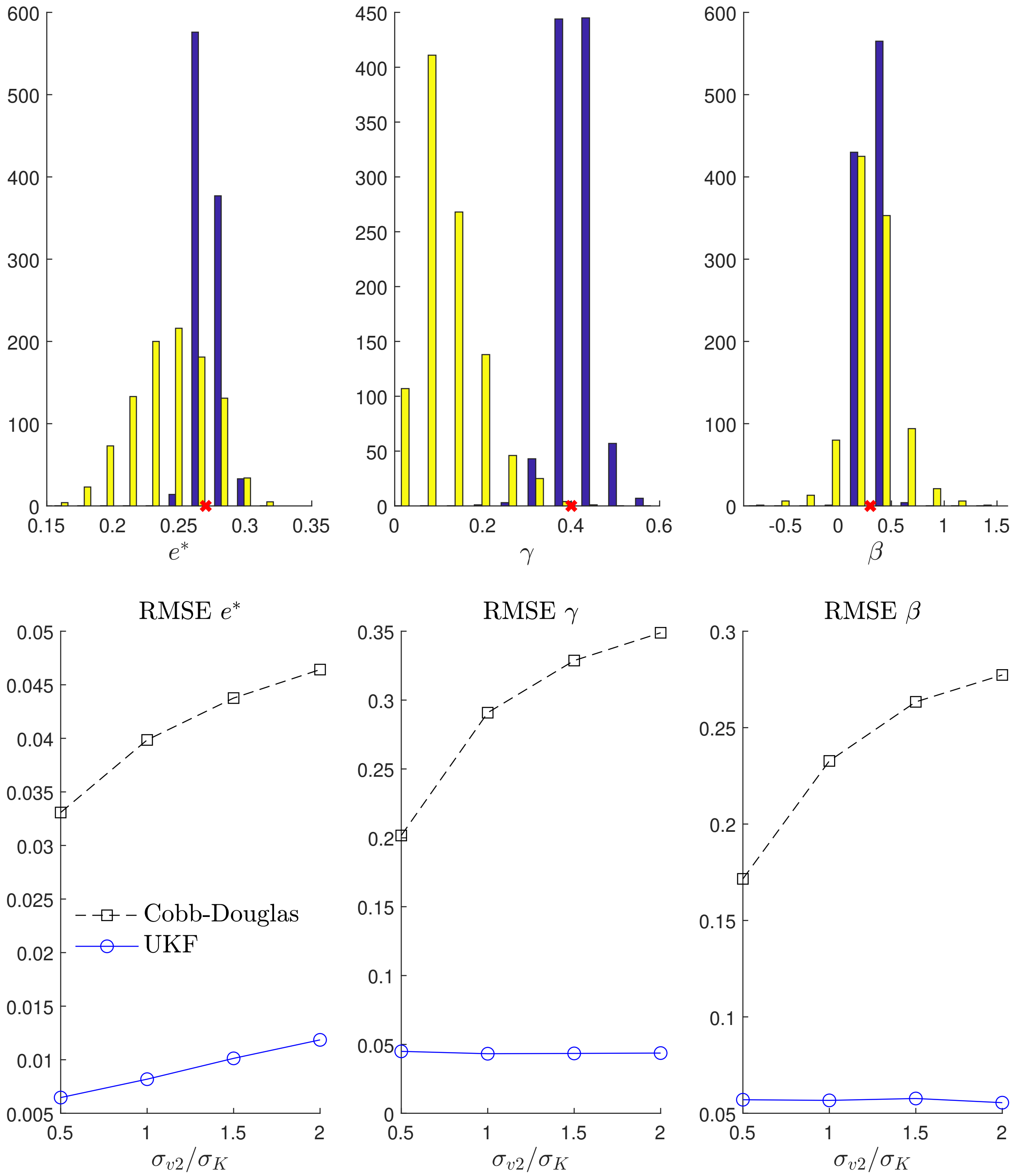

Fig. 3.11 **Monte Carlo simulation.** Upper graphs: distribution of estimates of efficiency e^*, capital elasticity γ, and labour elasticity β, using the Cobb–Douglas log-regression (yellow bars) and maximum likelihood with unscented Kalman filter (blue bars), based on 1,000 simulated data panels. Red crosses indicate the true parameter values. Lower graphs: root mean square error of parameter estimates for different levels of noise-to-signal ratio which is defined as standard deviation of measurement error of capital stock, σ_{v2}, over volatility of capital shock, σ_K. See Appendix 3.C for details of the Monte Carlo simulation.

Table 3.1 Definitions and descriptive of variables

This table presents the definitions (Panel A) and the descriptive statistics (Panel B) of the main variables used in the analysis. The descriptive statistics are: Number of observations (N); mean; standard deviation; and the percentiles p5, p25, p50, p75 and p95. The sample covers the period 1971 to 2019.

Panel A: Variable definition

Variable name	Variable definition
Earnings	Annual cash flow from operations gross of intangible investments, as defined by Peters and Taylor (2017b): Ebitda (oibdp) + R&D expense + 0.3 × SG&A expenses
Capital	Stock of tangible plus intangible capital, computed as in Peters and Taylor (2017b)
Investment	Investment in tangible & intangible assets, as defined by Peters and Taylor (2017b): Capex + R&D expense + 0.3 × SG&A expenses
Labor	Total number of employees (emp) times the annual average salary in the four industry groups in the 5-industry Fama and French (1997) classification: Consumer Goods, Manufacturing, Technology, and Healthcare
Hiring	Year-on-year change in the number of employees (emp_t-emp_{t-1}) plus the average number of employees leaving the company, estimated as emp times the US average annual separation from the U.S. Bureau of Labor Statistics
Hiring costs	*Hiring* times the average salary in the sector on the same year
Markup	Marginal cost markup by De Loecker et al. (2020b)
Size	Logarithm of the book value of total assets (at, in $M)
Initial assets	First available observation of the Book value of total assets (at, in $M) for each firm
ln(Sales)	Logarithm of annual sales (sale, in $M)
Sales growth	$ln(Sales)_t - ln(Sales)_{t-1}$
Age at IPO	Offer date year - Founding year, Field-Ritter dataset (Field and Karpoff, 2002; Loughran and Ritter, 2004)
Public life length	Duration of the firm's spell in Compustat in years

Panel B: Descriptive statistics

	N	mean	sd	p5	p25	p50	p75	p95
Earnings-to-initial assets	193,883	1.61	5.80	−0.48	0.08	0.31	0.88	6.55
Capital-to-initial assets	192,463	8.43	26.55	0.30	0.89	1.77	4.77	31.89
Labor-to-initial assets	166,732	4.46	15.16	0.03	0.28	0.77	2.25	17.31
Investment/Capital	189,430	0.23	0.18	0.04	0.10	0.18	0.29	0.61
Hiring/Labor	146,192	0.03	0.32	0.00	0.00	0.05	0.16	0.43
Markup	148,346	1.52	1.03	0.61	0.99	1.23	1.66	3.46
ROA	194,640	−0.12	0.48	−0.90	−0.09	0.02	0.07	0.17
Size	195,097	4.35	2.51	0.40	2.53	4.22	6.06	8.75
Age at IPO	84,878	19.76	25.38	1.00	5.00	10.00	22.00	79.00
Public life length	210,584	17.82	10.92	5.00	9.00	15.00	25.00	40.00

Table 3.2 **Decomposition of standard deviations by industries or estimation groups**
This table shows the decomposition of the total standard deviation of firm characteristics into the between- and within-group standard deviations. Firms are grouped according to their 4-digit SIC code (SIC4), their 17-industry classifications in Fama and French (1997) (FF17), or allocated into groups of ten firms sorted by average annual cash flow growth rate within each 5 Fama and French (1997) industry ('Groups') and same decade of IPO. The data is for all yearly observations of the Compustat firms with at least (not necessarily consecutive) 10 years of cash flow data between 1971 and 2019. All other variables are defined in Table 3.1.

	Standard deviation					
	Within-			Between-		
	SIC4	FF17	Groups	SIC4	FF17	Groups
Earnings-to-initial assets	2.93	4.34	2.57	1.33	0.70	2.19
Capital-to-initial assets	13.21	20.53	12.61	6.25	3.36	9.30
Labor-to-initial assets	8.30	10.89	6.99	4.96	2.75	5.49
Investment-to-initial assets	1.99	3.11	2.21	0.93	0.62	1.52
Hiring-to-initial assets	1.17	1.39	1.08	0.53	0.29	0.60
Markup	0.50	0.68	0.76	0.34	0.23	0.56
ROA	0.32	0.43	0.40	0.11	0.12	0.27
Size	2.09	2.44	1.93	1.25	0.61	1.50
Age at IPO	20.22	28.44	11.16	21.55	6.40	18.19
Public life length	9.63	10.93	6.79	4.73	1.38	6.44

Table 3.3 **Summary of the model's parameters and policies estimates**
This table summarises the maximum likelihood estimates of the model equations (3.11)–(3.17). The model parameters and policies are estimated for each of the 1,346 groups of firms in Compustat between 1971 and 2019. The 5th, 25th, 75th and 95th percentiles are denoted by p5, p25, p75, and p95.

Panel A: Point estimates

	Mean	Standard Deviation	p5	p25	Median	p75	p95
1. Policies							
$\hat{e}^*$	0.29	0.20	0.00	0.17	0.27	0.38	0.64
$\hat{i}^*$	0.20	0.08	0.09	0.14	0.18	0.24	0.34
$\hat{h}^*$	0.15	0.09	0.06	0.09	0.13	0.17	0.32
2. Capital and labor stocks							
$\hat{\mu}_K$	0.08	0.10	-0.04	0.04	0.08	0.13	0.21
$\hat{\sigma}_K$	0.20	0.32	0.00	0.04	0.15	0.25	0.51
$\hat{\mu}_L$	0.03	0.18	-0.25	-0.01	0.05	0.11	0.21
$\hat{\sigma}_L$	0.69	4.03	0.00	0.17	0.33	0.53	1.26
3. Earnings elasticities to inputs							
$\hat{\gamma}$	0.56	0.32	0.00	0.30	0.63	0.85	1.00
$\hat{\beta}$	0.27	0.28	0.00	0.07	0.16	0.40	0.93

Panel B: Absolute value of t-statistics

	Mean	Standard Deviation	p5	p25	Median	p75	p95
$\hat{i}^*$	2.68	2.78	0.04	0.80	1.92	3.61	7.71
$\hat{h}^*$	1.96	2.09	0.02	0.49	1.38	2.68	6.00
$\hat{e}^*$	7.12	8.97	0.17	2.04	4.95	9.66	19.92
$\hat{\mu}_K$	6.93	7.94	0.34	2.17	4.77	9.19	20.08
$\hat{\sigma}_K$	6.73	7.24	0.30	2.16	4.75	9.05	20.25
$\hat{\mu}_L$	6.70	7.28	0.33	2.13	4.88	8.96	18.42
$\hat{\sigma}_L$	6.73	6.81	0.32	2.04	4.83	9.13	19.51
$\hat{\gamma}$	7.26	7.76	0.29	2.13	4.98	9.47	21.81
$\hat{\beta}$	6.83	7.66	0.21	1.98	4.81	8.83	20.44

Table 3.4 **Summary of the model's parameters and policies estimates by industry**
This table reports the mean and standard deviation of the maximum likelihood estimates of the model equations (3.11)–(3.17) for the four major industries in the 5-industry classification by Fama and French (1997). The model parameters and policies are estimated for each of the 1,346 groups of firms in Compustat between 1971 and 2019. For each group, the parameters are estimated over two periods: the decade when the IPO took place (D1) and the next decade (D2). For the first decade, groups include either firms that failed and were de-listed in that decade or firms that survived.

Panel A: Point estimates by decade

		Consumer Goods			Manufacturing		
		Failed	Survived		Failed	Survived	
		D1	D1	D2	D1	D1	D2
$\hat{e}^*$	Mean	0.26	0.38	0.35	0.28	0.38	0.32
	Std. Dev.	0.17	0.13	0.25	0.18	0.21	0.24
$\hat{i}^*$	Mean	0.29	0.25	0.17	0.25	0.20	0.15
	Std. Dev.	0.08	0.06	0.04	0.06	0.06	0.04
$\hat{e}^*/\hat{i}^*$	Mean	1.02	1.56	2.13	1.24	2.00	2.30
	Std. Dev.	0.74	0.58	1.80	0.86	1.16	1.70
$\hat{\sigma}_K$	Mean	0.10	0.02	0.03	0.07	0.04	0.04
	Std. Dev.	0.24	0.11	0.09	0.13	0.14	0.23
$\hat{\gamma}$	Mean	0.36	0.49	0.64	0.45	0.45	0.58
	Std. Dev.	0.31	0.28	0.31	0.34	0.30	0.33
Log(Age at IPO)	Mean	2.28	2.78	2.79	2.38	2.69	2.70
	Std. Dev.	1.18	1.22	1.18	1.19	1.27	1.25
Number of firms		192	1,132	1,480	120	868	1,048

		Technology			Healthcare		
		Failed	Survived		Failed	Survived	
		D1	D1	D2	D1	D1	D2
$\hat{e}^*$	Mean	0.44	0.52	0.46	0.22	0.41	0.32
	Std. Dev.	0.32	0.25	0.31	0.17	0.32	0.29
$\hat{i}^*$	Mean	0.37	0.32	0.21	0.30	0.31	0.19
	Std. Dev.	0.08	0.08	0.05	0.09	0.06	0.03
$\hat{e}^*/\hat{i}^*$	Mean	1.25	1.70	2.16	0.93	1.40	1.74
	Std. Dev.	0.90	1.03	1.40	0.78	1.12	1.50
$\hat{\sigma}_K$	Mean	0.10	0.02	0.02	0.06	0.04	0.03
	Std. Dev.	0.21	0.05	0.05	0.14	0.07	0.09
$\hat{\gamma}$	Mean	0.38	0.44	0.58	0.47	0.37	0.53
	Std. Dev.	0.31	0.31	0.31	0.35	0.30	0.34
Log(Age at IPO)	Mean	1.99	2.21	2.20	2.05	1.93	2.02
	Std. Dev.	0.81	0.86	0.85	0.98	0.89	0.84
Number of firms		367	1,728	2,146	55	470	700

(Table continues)

Table 3.4 *-continued*

Panel B: Changes in estimates between decades†

		Consumer Goods	Manufacturing	Technology	Healthcare
$\Delta\hat{e}^*/\hat{i}^*$	Mean	0.41***	0.29*	0.37***	0.41**
	Standard deviation	1.53	1.81	1.58	1.19
$\Delta\hat{\sigma}_K$	Mean	0.02**	0.02	0.002	-0.01
	Standard deviation	0.10	0.15	0.09	0.10
$\Delta\hat{\gamma}$	Mean	0.16***	0.13***	0.14***	0.17***
	Standard deviation	0.41	0.47	0.43	0.45
Number of groups		124	117	158	49

† Estimates followed by ***, **, and * are statistically different from zero with 0.01, 0.05, and 0.1 significance.

Table 3.5 Interdecadal changes in efficiency and investment policies

This table presents estimates from cross-sectional regressions of the change in the estimated efficiency-to-investment ratio, $\Delta e^*/i^*$, from the decade of the firm's IPO to the next, on binary variables indicating the decade in which the firms went public ($1\{\text{IPO in DD}\}$ for DD = 70s, 80s, 90s, 00s) and the interaction between these dummy variables and changes in the volatility of the capital stock, $\Delta\hat{\sigma}_K$, and changes in the elasticity of earnings to capital, $\Delta\hat{\gamma}$ during the same period. The fixed effect of the 70s IPO cohort is subsumed by the constant in the regression. Additional control variables (coefficients untabulated) are the changes to the volatility of the labor stock and the elasticity of earnings to the labor factor. Each regression includes all groups of firms in one of each of the four major industries in the Fama and French (1997) 5-industry classification. Robust standard errors are reported under each estimate in parentheses. Estimates followed by $***$, $**$, and $*$ have p-values lower than 0.01, 0.05, and 0.1.

	Consumer Goods	Manufacturing	Technology	Healthcare
Constant	0.556***	0.290	0.028	0.390
	(0.162)	(0.189)	(0.180)	(0.316)
$1\{\text{IPO in 80s}\}$	-0.219	0.091	0.635***	0.658
	(0.237)	(0.267)	(0.225)	(0.491)
$1\{\text{IPO in 90s}\}$	1.011*	0.600*	1.021***	-0.398
	(0.603)	(0.349)	(0.308)	(0.448)
$1\{\text{IPO in 00s}\}$	0.156	0.084	0.692	2.599***
	(0.283)	(0.534)	(0.429)	(0.416)
$1\{\text{IPO in 70s}\} \times\Delta\hat{\sigma}_K$	-4.599	-1.330	0.902	8.966*
	(2.775)	(1.330)	(1.258)	(5.287)
$1\{\text{IPO in 80s}\}\times\Delta\hat{\sigma}_K$	7.808**	1.455	-0.591	-7.961
	(3.357)	(1.711)	(1.706)	(5.970)
$1\{\text{IPO in 90s}\}\times\Delta\hat{\sigma}_K$	-4.061	1.569	2.109	-8.621
	(6.998)	(1.838)	(2.448)	(5.467)
$1\{\text{IPO in 00s}\}\times\Delta\hat{\sigma}_K$	5.795**	-0.580	-12.316	-19.099**
	(2.867)	(1.862)	(8.941)	(8.105)
$1\{\text{IPO in 70s}\}\times\Delta\hat{\gamma}$	-1.756***	-0.121	-1.430***	-1.727*
	(0.465)	(0.632)	(0.502)	(0.910)
$1\{\text{IPO in 80s}\}\times\Delta\hat{\gamma}$	0.111	-0.840	-1.150**	-0.964
	(0.458)	(0.653)	(0.448)	(1.018)
$1\{\text{IPO in 90s}\}\times\Delta\hat{\gamma}$	-2.474**	-1.897***	-1.456**	0.114
	(1.241)	(0.672)	(0.558)	(0.843)
$1\{\text{IPO in 00s}\}\times\Delta\hat{\gamma}$	0.628	-5.211**	-1.478	8.553***
	(0.748)	(2.429)	(1.018)	(1.533)
Number of Observations	124	117	158	49
R^2	0.442	0.629	0.430	0.422

Table 3.6 **Cross-sectional regressions of efficiency and investment policies**

This table presents estimates from cross-sectional regressions of the estimated efficiency, e^*, investment, i^*, and efficiency-to-investment ratio, e^*/i^* on binary variables indicating the decade in which the firms went public, i.e., $1\{\text{IPO in DD}\}$ for DD = 80s, 90s, 00s, the volatility of the capital stock, $\hat{\sigma}_K$, the elasticity of earnings to capital, during the same period. Each regression controls for industry fixed effects using the Fama and French (1997) 5-industry classification. The constant subsumes the fixed effects of the 70s IPO cohort and the 5th industry ('Other'). The parameters are estimated over two periods: the decade when the IPO took place, and the next decade. Standard errors clustered at the group level are reported under each estimate in parentheses. Estimates followed by $***$, $**$, and $*$ have p-values lower than 0.01, 0.05, and 0.1.

	Failed firms, IPO decade			Survivors, IPO decade			Survivors, Next decade		
	$\hat{e}^*$	$\hat{i}^*$	$\hat{e}^*/\hat{i}^*$	$\hat{e}^*$	$\hat{i}^*$	$\hat{e}^*/\hat{i}^*$	$\hat{e}^*$	$\hat{i}^*$	$\hat{e}^*/\hat{i}^*$
Constant	0.369***	0.208***	1.831***	0.388***	0.251***	1.507***	0.653***	0.203***	3.730***
	(0.122)	(0.044)	(0.342)	(0.045)	(0.014)	(0.212)	(0.077)	(0.011)	(0.427)
$\hat{\sigma}_K$	0.054	0.039	-0.018	-0.102	-0.056**	0.128	-0.069	0.013	-0.317
	(0.098)	(0.032)	(0.293)	(0.082)	(0.023)	(0.587)	(0.063)	(0.013)	(0.362)
$\hat{\gamma}$	0.075	-0.006	0.124	-0.205***	-0.001	-0.869***	-0.508***	-0.005	-3.026***
	(0.058)	(0.028)	(0.220)	(0.040)	(0.014)	(0.161)	(0.081)	(0.009)	(0.461)
$1\{\text{IPO in 80s}\}$	-0.288**	0.069*	-1.185***	0.028	0.015	0.069	0.043	-0.016**	0.275**
	(0.116)	(0.040)	(0.290)	(0.026)	(0.010)	(0.108)	(0.026)	(0.007)	(0.126)
$1\{\text{IPO in 90s}\}$	-0.180	0.047	-0.753***	-0.008	-0.003	0.094	0.028	-0.040***	0.584***
	(0.113)	(0.040)	(0.284)	(0.023)	(0.009)	(0.102)	(0.031)	(0.007)	(0.179)
$1\{\text{IPO in 00s}\}$	-0.320***	0.018	-1.068***	-0.092***	-0.042***	0.015	-0.061	-0.056***	0.327
	(0.120)	(0.046)	(0.331)	(0.031)	(0.013)	(0.133)	(0.042)	(0.008)	(0.229)
Consumer Goods	0.004	0.055***	-0.222	0.061**	0.034***	0.005	0.069*	0.023***	0.206
	(0.044)	(0.016)	(0.208)	(0.025)	(0.010)	(0.137)	(0.038)	(0.006)	(0.249)
Manufacturing	0.013	0.019	-0.037	0.058**	-0.010	0.416**	0.026	-0.005	0.271
	(0.045)	(0.015)	(0.220)	(0.028)	(0.010)	(0.162)	(0.037)	(0.006)	(0.219)
Technology	0.167***	0.128***	-0.030	0.205***	0.106***	0.162	0.157***	0.054***	0.221
	(0.050)	(0.015)	(0.204)	(0.030)	(0.011)	(0.147)	(0.041)	(0.007)	(0.206)
Healthcare	-0.052	0.069*	-0.393	0.074	0.087***	-0.194	0.021	0.034***	-0.242
	(0.055)	(0.037)	(0.283)	(0.050)	(0.012)	(0.206)	(0.051)	(0.007)	(0.279)
Log(Age at IPO)	0.024***	-0.012***	0.115***	0.011***	-0.011***	0.126***	-0.006	-0.007***	0.032
	(0.008)	(0.003)	(0.030)	(0.004)	(0.002)	(0.021)	(0.005)	(0.001)	(0.032)
Observations	839	839	839	2,368	2,368	2,368	3,063	3,063	3,063
R^2	0.183	0.359	0.103	0.235	0.393	0.143	0.257	0.367	0.244

Table 3.7 **Firm policies and product market outcomes during the IPO decade**
This table presents estimates from cross-sectional regressions of the De Loecker et al. (2020b) price-marginal cost markup (Panel A) or the logarithm of total annual sales (Panel B) on the estimates of efficiency, e^* and the investment rate, i^*, during the decade in which the firm went public. Each specification includes cohort fixed effects (IPO in the 70s, 80s, 90s or 00s) and industry fixed effects following the 5-industry classification by Fama and French (1997). The number in brackets under each coefficient is its economic significance, computed as the product of the coefficient times its associated variable's sample standard deviation. Robust standard errors are reported in parentheses under each coefficient. Estimates followed by $***, **$, and $*$ have p-values lower than 0.01, 0.05, and 0.1.

Panel A: Markup

	Survivors	Failed	All firms	Survivors	Failed	All firms
$\hat{e}^*$	0.338***	0.702***	0.470***	0.345**	0.642***	0.444***
	[0.080]	[0.166]	[0.111]	[0.082]	[0.152]	[0.105]
	(0.124)	(0.154)	(0.0897)	(0.166)	(0.229)	(0.129)
$\hat{i}^*$	1.201***	-0.131	0.737***	0.806*	-0.165	0.526
	[0.106]	[-0.011]	[0.064]	[0.070]	[-0.014]	[0.046]
	(0.352)	(0.537)	(0.281)	(0.471)	(0.872)	(0.424)
Log(Age at IPO)				-0.074***	0.039	-0.043**
				[-0.083]	[0.045]	[-0.048]
				(0.027)	(0.033)	(0.021)
Observations	2,812	1,614	4,426	1,691	786	2,477
R^2	0.052	0.079	0.057	0.084	0.124	0.093

Panel B: Log(Sales)

	Survivors	Failers	All firms	Survivors	Failers	All firms
$\hat{e}^*$	1.579***	2.347***	2.088***	1.194***	1.449***	1.274***
	[0.374]	[0.556]	[0.495]	[0.283]	[0.343]	[0.302]
	(0.133)	(0.175)	(0.103)	(0.153)	(0.200)	(0.121)
$\hat{i}^*$	-9.329***	-4.996***	-8.468***	-5.808***	-3.420***	-5.242***
	[-0.812]	[-0.435]	[-0.737]	[-0.505]	[-0.298]	[-0.456]
	(0.411)	(0.514)	(0.318)	(0.528)	(0.613)	(0.403)
Log(Age at IPO)				0.521***	0.482***	0.517***
				[0.589]	[0.545]	[0.584]
				(0.039)	(0.057)	(0.032)
Observations	5,588	2,735	8,323	2,336	833	3,169
R^2	0.281	0.238	0.266	0.357	0.285	0.347

Table 3.8 Firm policies and product market outcomes after the IPO decade
This table presents estimates from cross-sectional regressions of the De Loecker et al. (2020b) price-marginal cost markup, the logarithm of total annual sales, and sales growth from the IPO decade to the next on the estimates of efficiency, e^* and the investment rate, i^*, during the decade after the IPO decade. Each specification includes cohort fixed effects for the IPO decade (70s, 80s, 90s or 00s) and industry fixed effects based on the 5-industry classification by Fama and French (1997). The number in brackets under each coefficient is its economic significance, computed as the product of the coefficient times its associated variable's sample standard deviation. Robust standard errors are reported in parentheses under each coefficient. Estimates followed by $***, **$, and $*$ have p-values lower than 0.01, 0.05, and 0.1.

	Markup		Log Sales		Sales Growth	
$\hat{e}^*$	0.427***	0.524***	1.468***	1.220***	0.598***	0.561***
	[0.116]	[0.142]	[0.398]	[0.331]	[0.162]	[0.152]
	(0.084)	(0.123)	(0.101)	(0.117)	(0.059)	(0.081)
$\hat{i}^*$	0.351	-0.238	-12.59***	-9.205***	0.516*	-0.479
	[0.020]	[-0.013]	[-0.704]	[-0.515]	[0.029]	[-0.027]
	(0.382)	(0.574)	(0.566)	(0.715)	(0.284)	(0.461)
Log(Age at IPO)		-0.066***		0.408***		-0.177***
		[-0.077]		[0.479]		[-0.208]
		(0.018)		(0.034)		(0.018)
Observations	5,384	2,795	7,001	3,048	6,156	2,600
R^2	0.073	0.099	0.23	0.303	0.040	0.078

Table 3.9 Predictive regressions of product market outcomes

This table presents estimates from regressions of the De Loecker et al. (2020b) price-marginal cost markup (Panel A), the logarithm of total annual sales (Panel B), and sales growth (Panel C) in Period 1 (0 to 5 years of the decade after IPO), Period 2 (6 to 10 years), and Period 3 (11 to 15 years) on the estimates of efficiency, e^* and the investment rate, i^*, during the IPO decade. Each specification includes cohort fixed effects for the IPO decade (70s, 80s, 90s or 00s) and industry fixed effects based on the 5-industry classification by Fama and French (1997). The coefficients of each regression are estimated by OLS or with a Heckman (1979) correction for sample selection, where the selection equation is given by the probability that a firm survives its IPO decade. Instruments include estimates of deep parameters (σ_K and μ_K) and the St. Louis FED probability of a recession in the month following the firm's IPO. The number in brackets under each coefficient is its economic significance, computed as the product of the coefficient times its associated variable's sample standard deviation. Robust standard errors are reported in parentheses under each coefficient. Estimates followed by $***$, $**$, and $*$ have p-values lower than 0.01, 0.05, and 0.1.

Panel A: Markup

	Period 1		Period 2		Period 3	
	OLS	Heckman	OLS	Heckman	OLS	Heckman
$\hat{e}^*$	0.480***	0.427***	0.376***	0.287**	0.328***	0.170
	[0.114]	[0.010]	[0.089]	[0.068]	[0.079]	[0.040]
	(0.109)	(0.149)	(0.098)	(0.144)	(0.119)	(0.182)
$\hat{i}^*$	0.921***	0.927**	0.772***	1.016***	1.204***	1.527***
	[0.081]	[0.081]	[0.068]	[0.089]	[0.106]	[0.134]
	(0.284)	(0.419)	(0.260)	(0.392)	(0.329)	(0.527)
Observations	4,320	3,226	3,741	2,902	2,152	2,068
R^2	0.064		0.09		0.126	

Panel B: Log(Sales)

	Period 1		Period 2		Period 3	
	OLS	Heckman	OLS	Heckman	OLS	Heckman
$\hat{e}^*$	1.963***	1.304***	2.261***	1.480***	2.274***	0.842**
	[0.466]	[0.309]	[0.536]	[0.351]	[0.539]	[0.200]
	(0.136)	(0.211)	(0.160)	(0.246)	(0.229)	(0.363)
$\hat{i}^*$	-8.505***	-5.899***	-8.966***	-5.648***	-9.598***	-5.865***
	[-0.746]	[-0.517]	[-0.786]	[-0.495]	[-0.842]	[-0.514]
	(0.409)	(0.681)	(0.467)	(0.760)	(0.676)	(1.059)
Observations	5,625	3,506	4,679	3,103	2,724	2,236
R^2	0.266		0.247		0.223	

(Table continues)

Table 3.9 *-continued*

Panel C: Sale Growth

	Period 1		Period 2		Period 3	
	OLS	Heckman	OLS	Heckman	OLS	Heckman
$\hat{e}^*$	0.374***	0.395***	0.672***	0.634***	0.743***	0.797***
	[0.089]	[0.094]	[0.160]	[0.150]	[0.176]	[0.189]
	(0.066)	(0.098)	(0.107)	(0.159)	(0.165)	(0.291)
$\hat{i}^*$	0.962***	0.756***	0.555**	0.473	-0.235	-0.044
	[0.084]	[0.066]	[0.049]	[0.042]	[-0.021]	[-0.004]
	(0.175)	(0.283)	(0.280)	(0.449)	(0.444)	(0.770)
Observations	5,567	3,480	4,623	3,080	2,700	2,225
R^2	0.028		0.034		0.027	

Table 3.10 Optimal e^*, i^* and the Investment CAPM betas

This table presents estimates from cross-sectional regressions of the betas for investment, $\beta_{I/A}$, profitability, β_{ROE}, and size, β_{ME}, on the estimates of efficiency, e^*, investment, i^*, and the elasticity of earnings to capital, $\hat{\gamma}$. Each specification also includes cohort fixed effects for the IPO decade (70s, 80s, 90s or 00s) and industry fixed effects based on the 5-industry classification by Fama and French (1997). The constant term subsumes the fixed effect of the 5th industry ('Other'). Robust standard errors are reported in parentheses under each coefficient. The betas for investment, profitability and size are obtained from the time series regressions of the portfolio returns on the investment, profitability and size factors calculated by Hou et al. (2015), controlling for market returns. We form portfolios of stocks based on our grouping of firms (Section 3.3.5) and consider the monthly returns of these portfolios throughout our sample period, from 1971 to 2019. Estimates followed by $***$, $**$, and $*$ have p-values lower than 0.01, 0.05, and 0.1.

	$\beta_{I/A}$	β_{ROE}	β_{ME}
$\hat{e}^*$	-0.080	0.710***	-0.310**
	(0.168)	(0.145)	(0.121)
$\hat{i}^*$	-1.058**	-2.013***	0.920***
	(0.532)	(0.463)	(0.349)
$\hat{\gamma}$	-0.125	0.364***	-0.110
	(0.103)	(0.091)	(0.073)
Consumer Goods	-0.056	0.085	0.008
	(0.010)	(0.084)	(0.071)
Manufacturing	0.018	-0.126	-0.023
	(0.101)	(0.086)	(0.070)
Technology	-0.765***	-0.345***	0.020
	(0.102)	(0.090)	(0.073)
Healthcare	-0.737***	0.017	0.319***
	(0.122)	(0.094)	(0.082)
Constant	0.541***	-0.341**	0.843***
	(0.168)	(0.147)	(0.120)
Observations	1,315	1,315	1,315
R^2	0.154	0.111	0.052

APPENDIX

3.A. Model Solution and Robustness of Policies

This section discusses the solution of the HJB equation (3.6) and the robustness of the optimal policies to various specifications of the cost function and shock correlations.

3.A.1. Solving the HJB Equation

Following the standard approach, we first guess the functional form of the value function and then verify that it satisfies the HJB equation. The guessed functional form is $V(K,L) = cK^{\gamma}L^{\beta}$. Then, plugging the partial derivatives of V and the optimal polices (3.7) in the HJB equation (3.6) gives the following equation in c

$$\begin{aligned} rc = \frac{1}{\lambda_e} - \left(\frac{1}{2\lambda_e} + \frac{c^2\gamma^2}{2\lambda_K} + \frac{c^2\beta^2}{2\lambda_L}\right) + c\gamma\left(\frac{c\gamma}{\lambda_K} - \delta_K\right) + c\beta\left(\frac{c\beta}{\lambda_L} - \delta_L\right) \\ + \frac{1}{2}c\gamma(\gamma-1)\sigma_K^2 + \frac{1}{2}c\beta(\beta-1)\sigma_L^2 \end{aligned} \tag{3.20}$$

where the terms $K^{\gamma}L^{\beta}$ canceled out. Rearranging the equation as $ac^2 + bc + d = 0$, with

$$a = \frac{\gamma^2}{2\lambda_K} + \frac{\beta^2}{2\lambda_L} \tag{3.21}$$

$$b = -\gamma\delta_K - \frac{1}{2}\gamma(1-\gamma)\sigma_K^2 - \beta\delta_L - \frac{1}{2}\beta(1-\beta)\sigma_L^2 - r \tag{3.22}$$

$$d = \frac{1}{2\lambda_e} \tag{3.23}$$

provides the usual solution of $c = (-b - \sqrt{\Delta})/(2a) > 0$, where $\Delta = b^2 - 4ad > 0$. Notice that $b < 0$. In essence, this solution of c corresponds to the first-best firm value in, e.g., Gryglewicz et al. (2020), which is attained when agency conflicts are absent in their setting. Second order conditions of the optimal policies e^*, i^*, h^* are given by

$$-C_{ee} = -\lambda_e K^{\gamma}L^{\beta}, \quad -C_{ii} = -\lambda_K K^{\gamma}L^{\beta}, \quad -C_{hh} = -\lambda_L K^{\gamma}L^{\beta}. \tag{3.24}$$

These conditions are all negative because $K > 0$ and $L > 0$ follow geometric Brownian motions in the steady state, which ensures that the objective function (3.5) is maximized.

The explicit solution of the constant c in the firm value $V(K,L) = cK^{\gamma}L^{\beta}$ allows us to characterize relevant sensitivities. Firm value is increasing in the efficiency effort $e^* = 1/\lambda_e$

$$\frac{\partial c}{\partial e^*} = -\frac{1}{2a}\frac{1}{2}\Delta^{-1/2}\frac{\partial \Delta}{\partial e^*} = -\frac{1}{2a}\frac{1}{2}\Delta^{-1/2}(-4a)\frac{1}{2} = \frac{1}{2}\Delta^{-1/2} > 0. \tag{3.25}$$

This in turn implies that, in the baseline model, investment and efficiency are complements

$$\frac{\partial i^*}{\partial e^*} = \frac{\gamma}{\lambda_K}\frac{\partial c}{\partial e^*} > 0 \tag{3.26}$$

recalling that $i^* = c\gamma/\lambda_K$. Moreover, the complementarity between investment and efficiency decreases with the volatility of capital shocks σ_K^2

$$\frac{\partial^2 i^*}{\partial e^*\,\partial\sigma_K^2} = \frac{\gamma}{\lambda_K}\left(-\frac{1}{4}\Delta^{-3/2}\frac{\partial\Delta}{\partial\sigma_K^2}\right) = \frac{\gamma}{\lambda_K}\left(-\frac{1}{4}\Delta^{-3/2}\right)2b\left(-\frac{1}{2}\gamma(1-\gamma)\right) < 0 \tag{3.27}$$

as $0 < \gamma < 1$, $\lambda_K > 0$, $\Delta > 0$, and $b < 0$.

Also, firm value is decreasing in the volatility of capital shocks σ_K^2

$$\frac{\partial c}{\partial\sigma_K^2} = \frac{\gamma(1-\gamma)}{4a}\left(1+\frac{b}{\sqrt{\Delta}}\right) < 0 \tag{3.28}$$

because $b/\sqrt{\Delta} < -1$, which in turn implies that the investment rate $i^* = c\gamma/\lambda_K$ is decreasing in σ_K^2

$$\frac{\partial i^*}{\partial\sigma_K^2} = \frac{\gamma}{\lambda_K}\frac{\partial c}{\partial\sigma_K^2} < 0. \tag{3.29}$$

3.A.2. Alternative Model Specifications

The optimal policies in the baseline model, namely efficiency e^*, investment rate i^*, and hiring rate h^*, are constant in the steady state. This section shows that the functional form of these policies is robust to a number of more general cost functions and model specifications, including correlated shocks and random firm exit. Although these extended specifications capture relevant economic aspects, such as cost complementarity or substitution, their estimation from real data is challenging because it would require some measurement of adjustment costs. Our objective here is not to estimate these cost functions but to show that in a more general model the optimal policies have the same form as in the baseline model.

Complementarity or substitution of inputs

Complementarity or substitution of inputs can be accommodated in the firm model by extending the cost function (3.4). As inputs we first consider efficiency and investment. Then, the cost function takes the form

$$C(e,i,h,K,L) = \left(\frac{\lambda_e}{2}e^2 + \frac{\lambda_K}{2}i^2 + \frac{\lambda_L}{2}h^2 + \lambda_{eK}\,e\,i\right)K^{\gamma}L^{\beta} \tag{3.30}$$

where the last term yields that $\partial C/(\partial e \partial i) \neq 0$ when $\lambda_{eK} \neq 0$. Specifically, if $\lambda_{eK} < 0$, then efficiency and capital are complements. Alternatively, if $\lambda_{eK} > 0$, efficiency and capital are substitutes. The latter case appears to be particularly relevant because it captures a resource constraint on the firm's capacity to increase inputs. In fact, an increase in investment i makes efficiency more costly because its marginal cost is given by

$$\frac{\partial C(e,i,h,K,L)}{\partial e} = (\lambda_e e + \lambda_{eK} i) K^\gamma L^\beta$$

which is increasing in i when $\lambda_{eK} > 0$. Similarly, an increase in efficiency makes investment more expensive when $\lambda_{eK} > 0$.

Even if the cost function (3.30) features an additional term, the functional form of the optimal polices are unchanged. The first order condition (FOC) for e is

$$\begin{aligned} K^\gamma L^\beta &= C_e \\ K^\gamma L^\beta &= (\lambda_e e + \lambda_{eK} i) K^\gamma L^\beta \end{aligned}$$

which implies that the efficiency e depends on the investment rate i and equals to

$$e = \frac{1}{\lambda_e} - \frac{\lambda_{eK}}{\lambda_e} i.$$

The second order condition for e is always negative, $-\lambda_e K^\gamma L^\beta < 0$. Similarly, the FOC for i is

$$\begin{aligned} V_K K &= C_i \\ c\gamma K^\gamma L^\beta &= (\lambda_K i + \lambda_{eK} s) K^\gamma L^\beta \end{aligned}$$

where in the second equality we used $V(K,L) = cK^\gamma L^\beta$. The investment rate i is then

$$i = \frac{c\gamma}{\lambda_K} - \frac{\lambda_{eK}}{\lambda_K} s.$$

The second order condition for i is always negative, $-\lambda_K K^\gamma L^\beta < 0$.

Finally, to jointly determine the optimal policies i^* and e^*, the system to be solved is given by

$$\begin{aligned} i^* &= \frac{c\gamma}{\lambda_K} - \frac{\lambda_{eK}}{\lambda_K} e^* \\ e^* &= \frac{1}{\lambda_e} - \frac{\lambda_{eK}}{\lambda_e} i^*. \end{aligned}$$

Solving for i^* gives

$$
\begin{aligned}
i^* &= \frac{c\gamma}{\lambda_K} - \frac{\lambda_{eK}}{\lambda_K} e^* \\
&= \frac{c\gamma}{\lambda_K} - \frac{\lambda_{eK}}{\lambda_K}\left(\frac{1}{\lambda_e} - \frac{\lambda_{eK}}{\lambda_e} i^*\right) \\
\left(1 - \frac{\lambda_{eK}^2}{\lambda_K \lambda_e}\right) i^* &= \left(\frac{c\gamma}{\lambda_K} - \frac{\lambda_{eK}}{\lambda_K}\frac{1}{\lambda_e}\right)
\end{aligned}
$$

which yields that i^* is constant in the steady state and consequently e^* is constant too, like in the baseline model.

In the cost function (3.30), replacing $\lambda_{eK} si$ by $\lambda_{eL} eh$ captures complementarity or substitution between efficiency and hiring, depending on the sign of λ_{eL}. Furthermore, adding the term $\lambda_{eL} eh$ in the bracket of the cost function (3.30) yields interactions among the three inputs, while preserving the functional form of the optimal policies.

Complementarity or substitution between capital and labor can be modeled by extending the cost function (3.4) to

$$
C(e,i,h,K,L) = \left(\frac{\lambda_e}{2} e^2 + \frac{\lambda_K}{2} i^2 + \frac{\lambda_L}{2} h^2 + \lambda_{KL}\, i\, h\right) K^\gamma L^\beta
$$

where the last term yields that $\partial^2 C/(\partial i \partial h) \neq 0$ when $\lambda_{KL} \neq 0$. Similar calculations as above show that the optimal policies retain their functional form. The first order condition (FOC) for i is

$$
\begin{aligned}
V_K K &= C_i \\
c\gamma K^\gamma L^\beta &= (\lambda_K\, i + \lambda_{KL} h) K^\gamma L^\beta
\end{aligned}
$$

which implies that the investment i is given by

$$
i = \frac{c\gamma}{\lambda_K} - \frac{\lambda_{KL}}{\lambda_K} h. \tag{3.31}
$$

Similarly, the FOC for h is

$$
\begin{aligned}
V_L L &= C_h \\
c\beta L^\gamma L^\beta &= (\lambda_L h + \lambda_{KL}\, i) K^\gamma L^\beta
\end{aligned}
$$

which implies that the optimal hiring of new work force h is given by

$$
h = \frac{c\beta}{\lambda_L} - \frac{\lambda_{KL}}{\lambda_L} i. \tag{3.32}
$$

Solving (3.31) and (3.32) for i^* and h^* gives that the optimal investment i^* is

$$i^* = \frac{c\gamma}{\lambda_K} - \frac{\lambda_{KL}}{\lambda_K}\left(\frac{c\beta}{\lambda_L} - \frac{\lambda_{KL}}{\lambda_L} i^*\right)$$
$$\left(1 - \frac{\lambda_{KL}^2}{\lambda_K \lambda_L}\right) i^* = \left(\frac{c\gamma}{\lambda_K} - \frac{\lambda_{KL} c\beta}{\lambda_K \lambda_L}\right).$$

That is, i^* is again constant in the steady state, which in turn gives that h^* is also constant. The FOC for e^*, and its solution, is the same as in the baseline model.

Correlated shocks

In the baseline model the Brownian shocks to capital and labor in (3.1) and (3.2) are uncorrelated. If these shocks are correlated, i.e., $corr(dW_{K,t}, dW_{L,t}) = \rho$, the additional term $V_{KL}\rho\sigma_K\sigma_L KL$ enters the HJB equation. Because this term does not depend on the control variables, FOCs and optimal polices are unchanged. In fact, guessing the functional form $V(K,L) = cK^\gamma L^\beta$, in the new HJB equation all the terms $K^\gamma L^\beta$ cancel out, and the constant c solves a similar equation to (3.20). Specifically, the new HJB equation with the additional term $V_{KL}\rho\sigma_K\sigma_L KL$ is

$$rV(K,L) = \sup_{e,i,h}\{K^\gamma L^\beta e - C(e,i,h,K,L) + V_K(i-\delta_K)K + V_L(h-\delta_L)L$$
$$+ \frac{1}{2}V_{KK}\sigma_K^2 K^2 + \frac{1}{2}V_{LL}\sigma_L^2 L^2 + V_{KL}\,\rho\,\sigma_K\sigma_L KL\}.$$

Plugging $V(K,L) = cK^\gamma L^\beta$ and the optimal polices in the HJB above gives that the constant c solves

$$rc = \frac{1}{\lambda_e} - \left(\frac{1}{2\lambda_e} + \frac{c^2\gamma^2}{2\lambda_K} + \frac{c^2\beta^2}{2\lambda_L}\right) + c\gamma\left(\frac{c\gamma}{\lambda_K} - \delta_K\right) + c\beta\left(\frac{c\beta}{\lambda_L} - \delta_L\right)$$
$$+ \frac{1}{2}c\gamma(\gamma-1)\sigma_K^2 + \frac{1}{2}c\beta(\beta-1)\sigma_L^2 + c\gamma\beta\rho\sigma_K\sigma_L.$$

Linear-quadratic adjustment cost function

The quadratic adjustment cost (3.4) implies that disinvesting, i.e., selling capital stock, generates no revenue. This assumption can be relaxed by considering a linear-quadratic cost function

$$C(e,i,h,K,L) = \frac{\lambda_e}{2}e^2 K^\gamma L^\beta + \frac{\lambda_K}{2}i^2 K^\gamma L^\beta + \frac{\lambda_L}{2}h^2 K^\gamma L^\beta + \alpha_K i K^\gamma L^\beta$$

where the last term can induce negative costs, i.e., revenues, when adjusting the investment rate i. The FOC for i is

$$V_K K = \lambda_K i K^\gamma L^\beta + \alpha_K K^\gamma L^\beta$$

and plugging in $V_K K = c\gamma K^{\gamma} L^{\beta}$ gives the optimal investment is

$$i^* = \frac{c\gamma}{\lambda_K} - \frac{\alpha_K}{\lambda_K}.$$

The investment rate i^* is constant in the steady state like in the baseline model. FOCs and policies of the other inputs are unchanged.

Random firm exit

Firms can randomly exit Compustat because of, e.g., default or merger and acquisition. This section shows that the functional form of the optimal policies, i.e., efficiency e^*, investment i^*, and hiring h^*, remain unchanged when the distribution of the random exit time is time-homogeneous.

Let τ denote the random time horizon over which management can operate firm assets, called random time in short. Assume that the hazard rate $\rho(t)$ of the random time is constant

$$\rho(t) = \lim_{\Delta \to 0} \frac{P[\tau \in (t, t+\Delta) | \tau \geq t]}{\Delta} = \overline{\rho}$$

and therefore τ is a Poisson random time with survivor function $S(t) = P[\tau \geq t] = \exp(-\overline{\rho}\, t)$. The objective function then becomes

$$V(K_0, L_0) = \sup_{e,i,h} \mathbb{E} \int_0^{\tau} \exp(-rt) \left(K_t^{\gamma} L_t^{\beta} \, dA_t - C(e_t, i_t, h_t, K_t, L_t) \, dt \right) \tag{3.33}$$

where the random time τ replaces the infinite time horizon in (3.5) in the time integral. We proceed in two steps: first, we make explicit the expectation in (3.33) with respect to the distribution of the random time and then, using an integration by parts, we transform the stochastic time horizon problem in (3.33) into an infinite horizon problem like in (3.5).

Let $F(t)$ be the cumulative distribution of function of τ, thus $F(t) = 1 - S(t)$. Define

$$\mathscr{U}(t) = \int_0^t \exp(-ru) \left(K_u^{\gamma} L_u^{\beta} \, e_u - C(e_u, i_u, h_u, K_u, L_u) \right) du$$
$$\mathscr{V}(t) = -S(t).$$

The objective function (3.33) then becomes

$$
\begin{aligned}
V(K_0, L_0) &= \sup_{e,i,h} \mathbb{E}\, \mathscr{U}(\tau) \\
&= \sup_{e,i,h} \mathbb{E} \int_0^\infty \mathscr{U}(t)\, dF(t) \\
&= \sup_{e,i,h} \mathbb{E} \int_0^\infty \mathscr{U}(t)\, d\mathscr{V}(t) \\
&= \sup_{e,i,h} \mathbb{E} \left[\mathscr{U}(t)\, \mathscr{V}(t) \Big|_0^\infty - \int_0^\infty \mathscr{V}(t)\, d\mathscr{U}(t) \right] \\
&= \sup_{s,i,h} \mathbb{E} \left[- \int_0^\infty \mathscr{V}(t)\, d\mathscr{U}(t) \right] \\
&= \sup_{e,i,h} \mathbb{E} \int_0^\infty \exp(-\overline{\rho} t) \exp(-rt) \Big(K_t^\gamma L_t^\beta\, e_t - C(e_t, i_t, h_t, K_t, L_t) \Big)\, dt
\end{aligned}
$$

where the second equality follows from making explicit the expectation of $\mathscr{U}(\tau)$ with respect to the distribution of τ only, the third equality follows from $dF(t) = -dS(t) = d\mathscr{V}(t)$, the fourth equality is the integration by parts, the fifth equality is discussed below, and the last equality follows from the definition of $\mathscr{V}(t)$ and $\mathscr{U}(t)$. The fifth equality is because, assuming the transversality condition, $\mathscr{U}(t)$ is bounded by a constant $\overline{U} > 0$ and therefore

$$
\lim_{t \to \infty} \mathscr{U}(t)\, \mathscr{V}(t) < \overline{U} \lim_{t \to \infty} \mathscr{V}(t) = 0
$$

as $\mathscr{V}(t) = -S(t)$ and goes to zero exponentially fast when $t \to \infty$. Also

$$
\lim_{t \to 0} \mathscr{U}(t)\, \mathscr{V}(t) = 0
$$

because $\mathscr{U}(t) \to 0$ and $\mathscr{V}(t) \to -1$ when $t \to 0$.

In sum, if management maximizes discounted cash flows over a stochastic horizon τ and the distribution of the random time is homogeneous, they act as if optimizing policies of an infinitely lived firm but discounting future cash flows at higher rate $(\overline{\rho} + r)$ rather than just at the risk-free rate r. Therefore, the functional form of the optimal policies solving (3.33) or (3.5) are identical.

3.B. Model Estimation with Unscented Kalman Filter

This section provides a detailed exposition of the estimation method used in Section 3.3.2. We describe the state space model, the unscented Kalman filter to compute the likelihood function, and how we handle missing observations.

3.B.1. The state space model

The state space model in (3.11)–(3.17) consists of a transition equation and a measurement equation. The transition equation describes the discrete-time dynamics of the latent state process, which is the unobserved capital and labor stocks providing services for production. The measurement equation describes the relation between the state process and the observed data (earnings, capital, labor, investment, hiring) of firms that share the same state process in each group. To facilitate the exposition, we use a standard notation in state space models, and present the model as if missing observations were absent (Appendix 3.B.3 discusses how we handle missing observations).

The transition equation describes the discrete time dynamic of the two-dimensional state process $x_t = [\log(K_t),\ \log(L_t)]'$, with $'$ denoting transposition,

$$x_{t+1} = \phi_0 + \phi_1 x_t + w_t \tag{3.34}$$

where $\phi_0 = [\mu_K\ \mu_L]'$, ϕ_1 is the identity matrix, $w_t \sim \mathcal{N}(0,Q)$, Q is a diagonal covariance matrix with entries σ_K^2 and σ_L^2. The measurement equation links the observed data to the state process and is given by

$$z_t = h(x_t) + v_t \tag{3.35}$$

where the measurement error $v_t \sim \mathcal{N}(0,R)$. We consider groups of $N = 10$ firms and for each firm we obtain five variables, i.e., operating earnings, capital, labor, investment and hiring. The fifty-dimensional vector z_t collects all the observed variables in every year t. We allow measurement errors on each variable to have their specific variance, $\sigma_{v,1}^2, \ldots, \sigma_{v,5}^2$, resulting in a block diagonal covariance matrix R. Denoting by $x_{1,t} = \log(K_t)$ and $x_{2,t} = \log(L_t)$ the two components of the state process, the nonlinear function $h(x_t)$ is given by

$$h(x_t) = [e^* \exp(\gamma x_{1,t}) \exp(\beta x_{2,t})\, \mathbf{1}',\ \exp(x_{1,t})\, \mathbf{1}',\ \exp(x_{2,t})\, \mathbf{1}',\ i^* \exp(x_{1,t})\, \mathbf{1}',\ h^* \exp(x_{2,t})\, \mathbf{1}']' \tag{3.36}$$

where $\mathbf{1}$ is an N-dimensional column vector of ones. The nonlinearity of $h(x_t)$ requires using the Unscented Kalman filter (UKF) to filter out x_t and to compute the likelihood function. Below we provide a brief discussion of the UKF, starting from the Kalman filter.

3.B.2. The Unscented Kalman filter

If the function $h(x_t)$ were linear, i.e., $h(x_t) = h_0 + h_1 x_t$, the Kalman filter would provide efficient estimates of the conditional mean and variance of the state vector. Let $\hat{x}_{t|t-1} =_{t-1} [x_t]$ and $\hat{z}_{t|t-1} =_{t-1} [z_t]$ denote the expectation of x_t and z_t, respectively, using information up to and including time $t-1$, and let $P_{t|t-1}$ and $F_{t|t-1}$ denote the corresponding error covariance matrices.

Furthermore, let $\hat{x}_t =_t [x_t]$ denote the expectation of x_t including information at time t, and let P_t denote the corresponding error covariance matrix. The Kalman filter consists of two steps: prediction and update. In the prediction step, $\hat{x}_{t|t-1}$ and $P_{t|t-1}$ are given by

$$\hat{x}_{t|t-1} = \phi_0 + \phi_1 \hat{x}_{t-1} \tag{3.37}$$

$$P_{t|t-1} = \phi_1 P_{t-1} \phi_1' + Q_t \tag{3.38}$$

where $\hat{z}_{t|t-1}$ and $F_{t|t-1}$ are in turn given by

$$\hat{z}_{t|t-1} = h_0 + h_1 \hat{x}_{t|t-1} \tag{3.39}$$

$$F_{t|t-1} = h_1 P_{t|t-1} h_1' + R. \tag{3.40}$$

In the update step, the estimate of the state vector is refined based on the difference between observed and predicted quantities, with $\hat{x}_t =_t [x_t]$ and P_t given by

$$\hat{x}_t = \hat{x}_{t|t-1} + K_t (z_t - \hat{z}_{t|t-1}) \tag{3.41}$$

$$P_t = P_{t|t-1} - K_t F_{t|t-1} K_t' \tag{3.42}$$

where K_t is the so-called Kalman gain, obtained by minimizing the trace of P_t with respect to K_t, and it is given by $K_t = P_{t|t-1} h_1' F_{t|t-1}^{-1}$.

In our setting, the function $h(x_t)$ is nonlinear, and the Kalman filter has to be modified. Non-linear state space models have traditionally been handled with the extended Kalman filter, which effectively linearizes the measure equation around the predicted state. In recent years the UKF has emerged as a superior alternative. Rather than approximating the measurement equation, it uses the true nonlinear measurement equation and approximates the distribution of the state vector with a deterministically chosen set of sample points, called "sigma points" that capture the true mean and covariance of the state vector. When propagated through the nonlinear function $h(x_t)$, the sigma points capture the mean and covariance of the data accurately to the 2nd order (3rd order for Gaussian states) for any nonlinearity.

Specifically, a set of $2L+1$ sigma points and associated weights are selected according to the following scheme

$$\begin{array}{rclcrcll}
\hat{\chi}_{t|t-1}^0 & = & \hat{x}_{t|t-1}, & & \omega^0 & = & \frac{\kappa}{L+\kappa} & \\
\hat{\chi}_{t|t-1}^i & = & \hat{x}_{t|t-1} + \left(\sqrt{(L+\kappa)P_{t|t-1}}\right)_i, & & \omega^i & = & \frac{1}{2(L+\kappa)}, & i = 1, \ldots, L \\
\hat{\chi}_{t|t-1}^i & = & \hat{x}_{t|t-1} - \left(\sqrt{(L+\kappa)P_{t|t-1}}\right)_i, & & \omega^i & = & \frac{1}{2(L+\kappa)}, & i = L+1, \ldots, 2L
\end{array} \tag{3.43}$$

where L is the dimension of $\hat{x}_{t|t-1}$, κ is a scaling parameter, ω^i is the weight associated with the i-th sigma point, and $\left(\sqrt{(L+\kappa)P_{t|t-1}}\right)_i$ is the i-th column of the matrix square root. Then, in the prediction step, (3.39) and (3.40) are replaced by

$$\hat{z}_{t|t-1} = \sum_{i=0}^{2L} \omega^i h(\hat{\chi}^i_{t|t-1}) \tag{3.44}$$

$$F_{t|t-1} = \sum_{i=0}^{2L} \omega^i (h(\hat{\chi}^i_{t|t-1}) - \hat{z}_{t|t-1})(h(\hat{\chi}^i_{t|t-1}) - \hat{z}_{t|t-1})' + R. \tag{3.45}$$

The update step is still given by (3.41) and (3.42), but with K_t computed as

$$K_t = \sum_{i=0}^{2L} \omega^i (\hat{\chi}^i_{t|t-1} - \hat{x}_{t|t-1})(h(\hat{\chi}^i_{t|t-1}) - \hat{z}_{t|t-1})' F^{-1}_{t|t-1}. \tag{3.46}$$

Finally, the log-likelihood function is given by

$$\sum_{t=1}^{T} -\frac{1}{2} \left[5N \log(2\pi) + \log |F_{t|t-1}| + (z_t - \hat{z}_{t|t-1})' F^{-1}_{t|t-1} (z_t - \hat{z}_{t|t-1}) \right] \tag{3.47}$$

where T is the time series length of the sample. Model estimates are obtained by maximizing the log-likelihood (3.47) with respect to the model parameters: e^*, c/λ_K, c/λ_L, γ, β, μ_K, μ_L, σ_K, σ_L, and the five variances of the measurement errors in the covariance matrix R. The procedure jointly returns parameter estimates and the filtered trajectory of the latent state variable $\hat{x}_t$.

3.B.3. Missing observations handled with unscented Kalman filter

A prominent feature of corporate data are missing observations. In our Compustat panel, 78% of firm-year observations are missing relative to a full balanced panel. Although the UKF is different from the standard Kalman filter, missing observations can be handled by applying the usual method in Kalman filtering; see Section 3 in Shumway and Stoffer (1982). For completeness we briefly recall the method.

Suppose that there are no missing observations in year t. Then, the measurement equation (3.35) holds. That is, z_t collects all the observable variables (operating earnings, capital, labor, investment, hiring) of the N firms in a year t. Suppose now that some data in year t is missing. The key idea is to "select" the components of the $5N$-dimensional vector z_t corresponding to the observed (not missing) data. This task is achieved by simply using a matrix S_t consisting of zeros and ones with dimension $M_t \times 5N$, where M_t is the number of observed variables. To illustrate, consider an extreme and unrealistic case in which only the first variable (operating earnings) of the first firm in z_t is available in year t. In that case, $S_t = (1, 0, \ldots, 0)$ is a $1 \times 5N$ row vector, $M_t = 1$ and $S_t z_t$ is the operating earning of that firm. If all variables of all N firms are available in year t, then S_t is a $5N \times 5N$ identity matrix.

The procedure to compute the log-likelihood value with missing observations is as follows. First, for each year t, construct the matrix S_t based on the position of observed variables in z_t.

Then, pre-multiply both sides of equation (3.35) by S_t and use this measurement equation to run the UKF. Finally, compute the log-likelihood in (3.47) replacing $5N$ by M_t, which is the effective number of observations used to compute the likelihood at time t.

The matrix S_t is time dependent and needs to be computed for each year t. This time dependence allows the procedure to accommodate missing observations of different variables in the $5N$-dimensional vector z_t as well as entry and exit of firms in the panel.

3.C. Monte Carlo simulation

This section presents a Monte Carlo simulation to compare parameter estimates based on the unscented Kalman filter and the Cobb–Douglas log-regression.

In the firm model given by equations (3.1) to (3.7) we set the model parameters as in Figure 3.1, i.e., $e^* = 0.27$, $\lambda_K = 2.5$, $\lambda_L = 4.5$, $\delta_K = 0.2$, $\delta_L = 0.1$, $\sigma_K = 0.35$, $\sigma_L = 0.3$, $\gamma = 0.4$, $\beta = 0.3$, $r = 0.045$. These parameters match average efficiency, investment and hiring rates estimated from real data in the empirical analysis. We use the model to simulate 1,000 data samples consisting of operating earnings, capital and labour stocks, investment and hiring rates for $N = 10$ firms over $T = 10$ years, mimicking the empirical work in Sections 3.3 and 3.4. For each simulated sample we obtain two sets of model parameters: (i) maximizing the likelihood function (3.18) using the unscented Kalman filter and (ii) running the Cobb–Douglas log-regression using positive earnings data only to obtain efficiency e^* and elasticities of capital and labour, γ and β. If capital and labour stocks were observed without error and earnings were always positive as $e^* K^\gamma L^\beta$, running the Cobb–Douglas regression in logs would allow to recover $\log(e^*)$, γ, and β exactly.[11]

The top three graphs in Figure 3.11 show the distribution of the parameter estimates of e^*, γ, and β. The likelihood-based method with the unscented Kalman filter provides highly accurate estimates, which is expected because it is the most efficient method to estimate the model parameters. In contrast, estimation results based on the Cobb–Douglas log-regression are largely inaccurate. Because capital and labour stocks are observed with error, and earnings are not always positive, estimates of all three parameters are severely biased toward zero, which consistent with the attenuation bias phenomenon induced by the errors-in-variables problem.[12]

In the above simulation, the inaccuracy of the Cobb–Douglas log-regression stems from two sources: (a) the measurement error in capital and labour stocks and (b) the usage of positive earnings only. To disentangle the impact of the two, we carry out the following exercise. We consider the measurement error in the capital stock, whose standard deviation is given by σ_{v2} in (3.14), the volatility of capital shocks σ_K, and then set the noise-to-signal ratio σ_{v2}/σ_K to 0.5, 1, 1.5, 2. All else equal, we re-run the above simulation for each value of the noise-to-signal

[11] Under the listed assumptions $\log(\text{earnings}) = \log(e^*) + \gamma \log(K) + \beta \log(L)$.

[12] Cobb–Douglas log-regressions provide estimates of $\log(e^*)$, rather than e^*. Estimates of $\log(e^*)$ substantially underestimate its true value, similarly to the estimates of e^* shown in Figure 3.11.

ratio. In the top graphs in Figure 3.11, σ_{v2}/σ_K was set to 0.5.

The bottom three graphs in Figure 3.11 report the root mean square error (RMSE) of e^*, γ, and β using the Cobb–Douglas log-regression and the maximum likelihood with unscented Kalman filter for various levels of the noise-to-signal ratio. The RMSE is defined as $\sqrt{\sum_{i=1}^{1000}(\hat{\theta}_i-\theta)/1000}$, where $\hat{\theta}_i$ is the parameter estimate in the i-th simulated sample and θ is the true parameter value, $\theta = e^*, \gamma, \beta$. Figure 3.11 shows that the RMSE of our method is an order of magnitude lower than the RMSE of the Cobb–Douglas regressions, irrespective of the level of the noise-to-signal ratio. Even for a low noise-to-signal ratio $\sigma_{v2}/\sigma_K = 0.5$, the RMSE of Cobb–Douglas regressions is 0.033 for the estimates of e^*, which results in a relative RMSE of 12% (=0.033/0.27). Estimation of elasticities is even less accurate. When $\sigma_{v2}/\sigma_K = 2$, the relative RMSE of γ from the Cobb–Douglas regression is 87% (=0.349/0.4), whereas our method has a relative RMSE of 11% (=0.044/0.4). While estimates based on the Cobb–Douglas regressions quickly and substantially deteriorate when the noise-to-signal ratio increases, estimates based on our method remain highly accurate and only in the case of e^* the RMSE slightly increases with the noise-to-signal ratio. Generally, our method has a RMSE four to seven times smaller. Finally, the gap between the RMSE of Cobb–Douglas regressions and of our method tends to widen as the the noise-to-signal ratio increases, particularly for the estimates of capital and labour elasticities, γ and β. This suggests that, as σ_{v2}/σ_K increases, the inaccuracy of Cobb–Douglas regressions is determined more by the measurement error problem of the capital stock than the usage of positive earnings only.

Chapter 4

Debt and Equity Crowdfunding in the Financial Growth Cycle*

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4.1. Introduction

It is becoming increasingly challenging for small businesses to take out loans. According to the Federal Reserve's April 2023 Senior Loan Officer Opinion Survey, a large fraction of banks reported tightening lending standards for firm loans, credit card loans, and home equity lines of credit — three of the most common sources of financing for startups — in the first quarter of 2023. This is particularly likely to impact small firms that do not qualify for public listing but are simultaneously unable to attract venture capital (VC) funding.[1] For these firms, alternative sources of capital are likely to become more important as catalysts of economic growth.

In this paper, we address two such alternatives: debt crowdfunding and equity crowdfunding. Since 2016, Regulation CF of the JOBS Act allows small businesses in the US to offer securities to individual investors via online crowdfunding platforms, with $530 million raised as of 2021. We investigate firms' decision to issue crowdfunded debt versus equity and how this choice relates to their stage in the financial growth cycle (Berger and Udell, 1998; Cole, Liang, and Zhang, 2020) as well as access to other sources of external financing. We find that firms that are less profitable, are in an earlier developmental stage, and have stronger ties to the

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[1] Nanda and Phillips (2022) report that only 0.5% (0.4%) of the firms in the US Survey of Business Owners use VC funding to start (expand) their business, while 22% (20%) use business loans from banks, 14% (18%) credit cards, and 7% (4%) home equity.

banking system are more likely to issue crowdfunded equity than debt. Successful crowdfunding is associated with increases in firm size, revenue, and profitability for early-stage firms, but not for late-stage firms. Our findings suggest that crowdfunding can alleviate capital constraints and foster growth for early-stage firms, but has a negligible impact on more mature firms that are already profitable.

In order to issue debt or equity via crowdfunding, an entrepreneur needs to file Form C with the Securities and Exchange Commission (SEC), disclosing information about the firms' financials, risk factors, business plan, leadership team and intended use of proceeds, as well as the type of security issued (debt or equity) and the crowdfunding goal (the amount that the entrepreneur intends to raise). The registrant also needs to select a crowdfunding platform (website) on which to issue securities, with platforms generally specializing in either equity or debt securities.[2] An important function of both Form C disclosure and platform due diligence (Cumming, Johan, and Zhang, 2019) is to reduce the information asymmetry that traditionally makes it difficult for entrepreneurs to secure external debt from providers other than banks (Diamond, 1984, 1991). If the entrepreneur manages to meet their crowdfunding goal, the campaign is considered successful and the securities are issued. If not, the funds are returned to the investors.[3]

We collect data from SEC Form C filings to construct a sample of 2,052 crowdfunding campaigns from 2016–2021, 1,697 of which are equity issuances and 355 debt. We supplement these data with firm-level characteristics from FactSet, SEC Form D filings on previous security issuances, and industry classifications from Capital IQ and web searches. We also include ZIP- and county-level data from the US Census Bureau, IPUMS (Manson et al., 2022), and the Federal Deposit Insurance Corporation (FDIC), among others.

We start by examining the factors associated with a firm's choice between debt and equity crowdfunding. The pecking order theory (Myers and Majluf, 1984) suggests that firms prefer debt over equity when seeking external capital due to lower information costs. Alternatively, the financial growth cycle framework proposed by Berger and Udell (1998) suggests that the hierarchy of financing options depends on firm size and development stage, as there are differ-

[2] Equity issuances most often consist of common stock or simple agreements for future equity (SAFE). SAFE contracts resemble warrants in that they give the investor rights to future shares when a priced investment round or liquidity event occurs, but do not immediately confer equity ownership unto the investor. Debt contracts vary; Some resemble traditional bonds with a predetermined yield and maturity, while others entitle investors to a percentage of the business's revenue each quarter until they reach a predetermined return on their investment or the note reaches maturity (thus resembling a royalty contract with maturity and capped payouts).

[3] The focus of our paper is securities crowdfunding (also referred to as return-based crowdfunding), which is distinct from project-based crowdfunding via platforms like Kickstarter. In the latter, individuals pledge capital in exchange for a specific product or service, whereas the former gives retail investors shares in the company itself (equity) or the right to pre-specified cash flows (debt). The incentives for entrepreneurs differ between these two types of crowdfunding; Project-based crowdfunding aims to deliver a specific product within a defined timeframe, while return-based crowdfunding is appropriate for investors with a long-run investment horizon due to the illiquidity of crowdfunded securities. Unless otherwise specified, "crowdfunding" in this paper refers to securities crowdfunding.

ent levels of information asymmetry and financial needs for each phase of growth. Following Cole, Liang, and Zhang (2020), we categorize firms into three stages of the financial growth cycle that are appropriate for smaller entrepreneurial firms: a first stage where firms have assets in place but do not generate revenue, a second stage where firms have positive revenue but are unprofitable, and a third stage where firms achieve profitability to generate positive revenue and net income. We find that the capital structure of crowdfunded firms tends to follow a growth cycle pattern. More specifically, early-stage startups are more likely than late-stage startups to fund themselves with equity crowdfunding. As firms move on from their introductory developmental phase, they tend to rely more on debt-based crowdfunding, consistent with improved financial stability and creditworthiness.

Next, we investigate how the availability of traditional bank financing is related to the firm's choice of crowdfunding offering. Previous studies in the banking literature document that banks are prone to establish lending relationships with borrowers located in close proximity to their branches and that lending to small businesses is usually restricted to local markets (Agarwal and Hauswald, 2010; Brevoort, Wolken, and Holmes, 2010; Nguyen, 2019). Likewise, the distance between entrepreneurs and offline early-stage investors, such as banks, venture capitalists, and angel investors, has been shown to be a barrier to small business financing (Stuart and Sorenson, 2003; Cumming and Dai, 2010). Since online funding platforms can reduce these distance-related costs, we hypothesize that debt crowdfunding can serve as a substitute for bank lending when the entrepreneur has limited access to traditional offline funding sources (Agrawal, Catalini, and Goldfarb, 2015; Vulkan, Åstebro, and Sierra, 2016).

Our results support the substitution hypothesis. We find that firms located in areas with access to a larger number of bank branches (proxying for access to bank loans) are more likely to issue crowdfunded equity. We also observe the same pattern for firms located in areas with higher house prices (proxying for access to home equity). To conclude our analysis, we investigate whether successful crowdfunding is associated with realized gains in firm size and performance. Theoretically, it is ex-ante ambiguous whether to expect crowdfunding to result in positive firm outcomes, i.e., whether entrepreneurs are willing and able to put the funding to productive use. For example, due to high information asymmetry and moral hazard in crowdfunding markets, entrepreneurs may be less competent, take on riskier projects, and be more likely to commit fraud than entrepreneurs seeking traditional sources of funding (Agrawal, Catalini, and Goldfarb, 2014).

To analyze the relationship between crowdfunding and firm growth, we compare firms that successfully issue crowdfunded debt or equity to a sample of matched private firms from Factset in a matched diff-in-diff setting (as in Boucly, Sraer, and Thesmar (2011)). We find that crowdfunding firms increase their total assets, revenue, and profitability relative to the control sample. We also show that this difference is largest for first-stage firms, with the relationship weakening as firms mature. While the change in profitability associated with crowdfunding is positive and significant for both first- and second-stage firms, it is insignificant for third-stage firms. Our results suggest that crowdfunding can improve operational performance for firms that are not yet profitable but has a negligible impact on more mature, profitable, firms.

Related literature. Our paper primarily contributes to two strands of literature. First, we add to the literature on securities crowdfunding (see Mochkabadi and Volkmann (2020) and Bollaert, Lopez-de Silanes, and Schwienbacher (2021) for recent surveys) and Regulation Crowdfunding (CF) of the Jumpstart Our Business Startups (JOBS) Act. This paper is, to our knowledge, the first to investigate the choice between issuing crowdfunded debt or equity as well as how firm characteristics relate to this decision. While several papers explore either debt or equity crowdfunding in isolation, what motivates firms to choose between these two security types has not previously been documented. The only other paper addressing equity and debt crowdfunding simultaneously that we are aware of is Cumming, Johan, and Reardon (2022), who show that equity offerings are more likely to be successful and raise more capital than debt offerings.

Previous empirical evidence on whether securities crowdfunding facilitates firm growth is limited and mixed. Using a sample of UK firms, Eldridge, Nisar, and Torchia (2021) find that equity crowdfunding is associated with improved return on assets (ROA) but not increased innovation activity. Havrylchyk and Mahdavi Ardekani (2020) do not observe any relationship between debt crowdfunding and sales growth, investment, employment, or profitability for a sample of French firms. Hornuf, Schmitt, and Stenzhorn (2017), Butticè, Di Pietro, and Tenca (2020), and Dolatabadi, Fracassi, and Yang (2021) show that successful equity crowdfunding campaigns are associated with a higher likelihood of subsequent venture capital funding and higher survival rates. Our results show that post-crowdfunding growth is related to the firm's growth cycle stage, which may partially reconcile why prior papers have observed positive effects associated with equity (early-stage) crowdfunding, but not debt (late-stage) crowdfunding.[4]

Second, we contribute to prior work on the capital structure and growth of small entrepreneurial firms (see Ewens and Farre-Mensa (2022) and Nanda and Phillips (2022) for recent surveys). Due to data limitations, most studies on entrepreneurial financing decisions focus on small, privately held firms using data from surveys like the Federal Reserve Board's Surveys of Small Business Finances or the Kauffman Firm Surveys (Berger and Udell, 1998; Coleman, 2002; Robb and Robinson, 2012; Cole and Sokolyk, 2018). Berger and Udell (1998) find that small firms rely more on debt financing during their early growth stages but decrease their reliance

[4]While this study focuses on existing firms' growth, other studies analyze whether crowdfunding is conducive to new business formation. Rashidi Ranjbar (2022) finds that the passage of both state-level crowdfunding legislation and Regulation CF increases the number of new business applications, but that only the former results in successful business formation. Lambert, Ralcheva, and Roosenboom (2022) show that project-based crowdfunding (Kickstarter) is positively associated with business formation and average establishment size at the county level.

on debt as they mature. Robb and Robinson (2012) show that young firms rely more on external debt financing and less on friends-and-family-based funding sources. More recently, Cole, Liang, and Zhang (2020) look at sources of debt financing for small firms that trade over-the-counter (OTC). We contribute by providing the first evidence on the relationship between growth cycle patterns for startups and crowdfunding decisions, as well as showing that growth outcomes following crowdfunding are related to the firm's growth cycle stage.

The rest of this article proceeds as follows. In Section 2, we describe the institutional framework that motivates the article. In Section 3, we describe the data and provide summary statistics. Sections 4 through 5 present the empirical analysis, and Section 6 concludes.

4.2. Institutional background

The JOBS Act, signed into law on April 5, 2012, aims to facilitate capital raising for startups and small businesses by allowing them to offer securities to a wider pool of investors at lower costs. On October 30, 2015, the SEC adopted the final rules for Regulation CF, which became effective on May 16, 2016. Under Regulation CF, US private firms can raise up to $1.07 million in a 12-month period by issuing debt or equity securities. As of 2021, the maximum aggregated offering amount in a 12-month period is increased to $5 million.

Prior to Regulation CF, debt and equity crowdfunding was limited to accredited investors, typically high-income or high-net-worth individuals. Regulation CF expands investment opportunities to non-accredited (retail) investors, allowing them to purchase debt or equity securities issued through crowdfunding. To comply with SEC requirements, issuers must disclose both quantitative and qualitative information by filing Forms C, C-U, and C-AR, making this information publicly available at least 21 days before the securities are sold. Additionally, the offering must be conducted through a broker-dealer or a SEC-registered portal, which is a new type of intermediary introduced by the JOBS Act.

The disclosure requirements in Regulation CF are designed to protect investors from fraud and ensure the reliability of the information provided by businesses. To mitigate the risk of fraudulent activities, the JOBS Act introduces three additional measures. First, it sets limits on the amount that individuals can invest annually (up to 10% of their income or net worth), thereby limiting potential losses. Second, it enables civil actions against issuers, directors, and officers who provide false or misleading statements. Third, it grants the SEC authority over funding portals to enforce regulations and mandates for both issuers and intermediaries.

4.3. Data

4.3.1. Data sources

Our primary data source is the Electronic Data Gathering, Analysis, and Retrieval system (EDGAR) operated by the SEC. EDGAR serves as the primary system for companies and other entities submitting documents under various securities acts. We construct a sample of crowdfunding security offerings in the US under Regulation CF from July 2016 to the end of 2021. Regulation CF requires companies issuing securities through crowdfunding to disclose Forms C and C-U with the SEC, investors, and the intermediary facilitating the offering. These filings detail the firms' financials, risk factors, business plan, leadership team, and intended use of proceeds, as well as the type of security issued (debt or equity) and the crowdfunding goal (the amount that the entrepreneur intends to raise). These filings allow us to record information about the issuing firms' financial statements at the time of the offering, one year prior to the offering, and, if the offering is successful, one year after the crowdfunding campaign (Form C-AR).

Our main sample of analysis is a cross-section of 2,052 firms that launched a crowdfunding campaign in 2016–2021. To exclude firms that are crowdfunding but have not yet formed, we require firms to have non-zero assets. We winsorize all continuous variables at the 2% and 98% tails. Since industry codes are not specified in Form C filings, we collect SIC codes using Capital IQ and via manual web searches. To get information about prior security issuances, we collect information from Form D filings in EDGAR. Firms that raise capital through private placement of securities under Regulation D are required to fill out Form D. These data allow us to get information about additional capital raised through institutional investors by firms in our sample. In particular, we are able to assess whether firms raise capital by issuing securities through other venues before and/or after the crowdfunding offering.

In order to investigate the relationship between crowdfunding and bank lending, we gather data on banks from the Board of Governors of the Federal Reserve System. These data provide information about the number of bank branches at the ZIP code or county level. We also collect the house price index (HPI) at the ZIP code level from Federal Housing Finance Agency). To construct a control group of private firms, we rely on FactSet. FactSet allows us to access information about private firms in the US from 2015 to 2021. We construct a matched control sample by matching crowdfunding firms in the year before they issue crowdfunding securities to FactSet firms using propensity score matching on industry (SIC-2), ROA, and total assets.

Finally, we supplement our analysis with macroeconomic variables and Census data at the ZIP-code level from the IPUMS National Historical Geographic Information System (NHGIS) (Manson et al., 2022). IPUMS NHGIS offers easy access to summary tables and time series of population, housing, agriculture, and economic data for various levels of US census geography.

In particular, we use data from the 2020 American Community Survey: 5-Year Data (2016-2020) for county-level control variables.

4.3.2. The US crowdfunding market

In this section, we describe the crowdfunding market governed by Regulation CF from 2016–2021. We start by presenting information about the number of total and successful offerings by year. Figure 4.1 shows that the number of security offerings increases from 192 in 2016 to 1,586 by 2021. The unconditional probability for a campaign to be successful remains fairly stable at around 40% during 2016–2020, but dips to 24% in 2021.

Figure 4.2 shows the quarterly amount successfully raised by crowdfunding firms in USD millions. Firms raised around $10 million in the third quarter of 2016, an amount which grows to $115 million by the fourth quarter of 2021, in part because Regulation CF was amended in 2021 to allow an increase in the maximum amount firms are allowed to raise via crowdfunding. In Panel B, we plot the average number of days that it takes a campaign to reach its goal. On average, it takes 150 days for a firm to meet its funding goal, but this figure starts to decline in 2021. The dramatic drop in the fourth quarter is mechanical: Since the sample ends in 2021, the closing date is recorded for only the fastest and most successful crowdfunding campaigns. Next, we provide a more granular analysis of crowdfunding intermediaries. As of 2021, more than 100 internet portals are registered with the SEC. Figure 4.3 plots the number of internet portals acting as intermediaries from 2016–2021. However, more than 70% of the offerings are intermediated by only eight portals and the two most popular portals (Wefunder and StartEngine) manage as much as 45% of the offerings (see Figure 4.4). Thus, even though the number of registered portals is large, the intermediaries market is heavily concentrated, likely because network effects attract issuers to platforms that already have a large investor base.

Finally, we are interested in the location and legal status of issuing firms. Figure 4.5 shows the number of offerings per county in our sample period. Most of the issuers are headquartered in California, Florida, New York, and Oregon. Furthermore, 60% of the companies are corporations and 38% limited liabilities companies.

4.3.3. Summary statistics

Table 4.1 presents summary statistics for our sample of 2,052 crowdfunding firms. The table is divided into three panels: issuing firm characteristics (Panel A), offering characteristics (Panel B), and macro variables (Panel C). Table 4.A.1 provides detailed definitions for all variables.

Panel A displays firm characteristic sample statistics for several variables: profitability (ROA), the size of the firm measured as the natural log of total assets (Size), cash holdings (Cash), leverage measured as total debt over total assets (Leverage), sales measured as the natural log of total sales (Log sales), firm age in a number of years (Age), and the number of employees measured as the natural log of the total number of employees (Log employees). Issuers tend to be small firms both in terms of size (mean assets are \$708,000 and median \$103,000) and number of employees (mean 9 employees and median 4). Comparing firms issuing debt and equity reveals that the former is on median smaller but has a higher fraction of large issuers (resulting in a higher average), with average (median) assets of \$1.07 million (\$66,000) versus \$632,000 (\$114,000) for equity issuers. Equity issuers also tend to be younger, more levered, and less profitable than debt issuers.

Panel B summarizes offering campaign characteristics, with the amount of funding sought (Amount offered), price per security (Price security), type of security offered (Type of security, where 1 is debt and 0 equity), whether the campaign was successful (Success), and whether the firm had previously raised capital from institutional or accredited investors (Previous Institutional Funding). Firms seek to raise \$63,000 on average (\$25,000 median), with an average security price of \$487 for debt and \$92 for equity. 17% of the issuances are debt versus 83% equity, and 37% of campaigns are successful. Notably, around 25% of the sample has previous funding from institutional or accredited investors according to Form D filings, with a smaller fraction of debt issuers (14%) than equity (27%).

Panel C presents information regarding macro variables. Bank Density is the natural log of the total number of bank branches within 150 miles of the issuer's location. Top Bank is a dummy variable that takes the value of 1 if the issuer is located in an area that is in the top quartile of the Bank Density distribution, and 0 otherwise. Total population, Median Income, Frac. White, and Num. of Establishment are variables at the county level. A comparison of debt and equity issuers suggests that debt issuers are headquartered in areas with more access to banks and slightly lower median income.

Finally, Table 4.2 shows the industry distribution (classified by SIC-2 code) of our full sample as well as the subsamples of debt and equity issuers. Business services (in particular computer software) is the largest industry among equity issuers (19%) and second largest among debt issuers (15%). Food products (often breweries and distilleries) and eating and drinking places (mostly restaurants) also account for a large fraction of debt issuers (29%) and a smaller, but still significant, fraction of equity issuers (12%). Other represented industries among equity (debt) issuers include miscellaneous retail and wholesale trade at 8% (8%), engineering, research, and management services at 4% (5%), amusement and recreation services at 4% (3%), and chemicals and allied products at 3% (2%).

4.4. The Choice of Debt versus Equity Crowdfunding

4.4.1. Crowdfunding and the Financial Growth Cycle

How do firms choose between debt and equity crowdfunding? The pecking order theory, as developed by Myers and Majluf (1984), predicts that if capital is needed for new investment opportunities, firms have a preference for internal financing over external financing due to adverse selection. When outside funds are needed, firms prefer debt over equity because debt issues are associated with lower information costs. Equity is seldom issued. However, this theory does not account for several broad patterns of corporate finance. In particular, small high-growth firms are typically thought to have significant information asymmetries, making them particularly susceptible to adverse selection problems. Frank and Goyal (2009) find evidence that such firms generally do not act in accordance with the pecking order theory.

In Table 4.3, we run cross-sectional firm-level OLS regressions with security choice (1 if debt, 0 if equity) as the dependent variable. The control variables include a set of firm characteristics (profitability, size, cash holdings, long-term leverage, and short-term leverage) as well as year and industry fixed effects varying by column. Columns 1–3 contain the full sample of 2,052 firms, 4–5 the subsample of successful issuers, and 6–7 the subsample of failed issuers. The table shows that more profitable firms are more likely to issue debt, which is consistent with them being better able to service debt than less profitable firms. We also find that larger issuers are more likely to issue equity crowdfunding, although this relationship is not statistically significant for the subsample of successful crowdfunders. Finally, we note that firms with higher leverage are more likely to issue equity than debt. This could have several potential explanations, including levered firms (1) not needing to turn to crowdfunding for debt funding since they already have access to bank lending (which we explore further in Section 4.2), (2) being unable to issue further debt due to borrowing constraints, or (3) using crowdfunding to reduce their leverage and bankruptcy risk.

As noted by Berger and Udell (1998), the pecking order hierarchy depends on the size and stage of development of the firm, as there are different levels of information asymmetry and financial needs for each phase of growth. We next investigate whether the likelihood of issuing debt crowdfunding increases as the firm progresses through the financial growth cycle. We define three growth cycle stages appropriate for startups following Cole, Liang, and Zhang (2020): a first stage where firms are pre-revenue, a second stage where firms have positive revenue but are not yet profitable (negative or zero net income), and a third stage where firms achieve profitability to generate positive revenue and net income. Since businesses establish more solid track records (reducing information asymmetry) and start to generate steady revenue streams as they progress through these stages, we expect debt crowdfunding to become a more viable financing option for these firms as they mature.

In Table 4.4, we run the same set of regressions as in Table 4.3, but add two additional independent variables: a dummy designating that the firm is a second-stage firm (revenue-generating but not profitable) and a dummy for third-stage firms (revenue-generating and profitable). Our results indicate a monotonic and positive relationship between stage and the likelihood of issuing debt: As per Column 3, firms in the second stage are 4.6pp likelier to issue debt over equity, and firms in the third stage are 13.3pp likelier. In other words, more mature firms with positive cash flows are more likely to choose debt crowdfunding when available, allowing them to access funding without relinquishing ownership or control of their business. In contrast, early-stage firms that have not started generating revenues are the most likely to opt for equity issuance. These startups do not have a track record of stable cash flows and may be more informationally opaque for investors, which makes debt financing less attractive.

In Table 4.A.2 of the Appendix, we present consistent results when using age as an alternative measure for the firm's financial growth cycle. There are several reasons why we use age to proxy for growth cycle stage only for robustness. Faff, Kwok, Podolski, and Wong (2016) argue that firm age is not a reliable indicator of a firm's growth cycle stage, as the time it takes for a firm to transition across growth cycle stages can vary by industry, and firms of the same age can learn at different rates based on their feedback mechanisms. Furthermore, using age as a proxy for the growth cycle stage assumes that a firm progresses linearly through the cycle, which may not be the case (Dickinson, 2011).

4.4.2. Crowdfunding and Access to Bank Lending

Next, we ask whether debt crowdfunding can act as a substitute for bank lending for borrowers with limited access to capital through traditional banking channels. A large body of research in banking establishes that banks constrain their lending to areas surrounding their bank branches, and that lending to small businesses is usually restricted to local markets (Agarwal and Hauswald, 2010; Brevoort, Wolken, and Holmes, 2010; Nguyen, 2019). Accordingly, areas with a higher concentration of bank branches are known to have more competitive banking markets, resulting in improved credit access. In the same vein, the distance between entrepreneurs and offline early-stage investors, such as banks, venture capitalists, and angel investors, has been shown to be a barrier to small business financing (Stuart and Sorenson, 2003; Cumming and Dai, 2010). Since online funding platforms can reduce these distance-related costs, crowdfunding is anticipated to improve the odds for entrepreneurs located in areas underserved by traditional offline funding sources to secure outside capital (Agrawal, Catalini, and Goldfarb, 2015; Vulkan, Åstebro, and Sierra, 2016).

To distinguish between the effects of bank access and demographic differences in loan demand, we follow a similar approach as Erel and Liebersohn (2022) and control for county fixed effects. These capture systematic differences in the financial environment across counties (e.g., local business cycle or economic factors). In addition, we control for plausible demand-side factors by adding local demographic and income controls such as median income, the proportion of the white population, the total population, and the number of establishments within each ZIP code. Our baseline regression specification is as follows:

$$Equity_{i,t} = \beta BankAccess_{t-1} + Controls_{z,t} + \varphi_t + \gamma_s + \delta_c + \varepsilon_{i,t} \tag{4.1}$$

where i, s, z, c and t index crowdfunding campaign, industry sectors, ZIP codes, counties, and time, respectively. We are primarily interested in β, the coefficient on bank access measurements. It is difficult to measure a firm's access to bank lending directly, which makes it necessary to apply proxies instead. We proxy for bank access using two different measures. The first is the log local house price index (HPI) measured at the ZIP code level. Home equity is one of the most frequent sources of funding for startups (Nanda and Phillips, 2022), so we expect HPI to be positively correlated with greater access to bank lending. The second measure is the number of bank branches within 150 miles. We also use a dummy equal to one if the firm is located in the top quartile of ZIP codes by the number of bank branches within 150 miles.

To investigate whether debt crowdfunding can substitute for bank lending, Table 4.5 presents similar cross-sectional regressions as in Tables 4.3 and 4.4, but with the addition of the HPI variable, controls for ZIP-level economic and demographic conditions, and county fixed effects. We observe a negative and significant relationship between local house prices and a firm's likelihood of issuing debt instead of equity. In Column (5), which controls for year, industry, and county fixed effects, we estimate that a one standard deviation increase in HPI corresponds to a 2.9% lower likelihood for a firm to choose debt financing. This suggests that as home values increase — and entrepreneurs have more home equity to tap for funding — firms become more likely to seek equity crowdfunding instead of debt.

In Table 4.6, we again address the same question but with the second proxy for bank access: the number of bank branches within 150 miles of the firm's headquarters. Column 1 shows that firms located in areas with more bank branches (proxying for better access to bank loans) are less likely to issue crowdfunded debt. One log-point increase in bank branches within 150 miles is associated with a decrease in the likelihood of obtaining crowdfunded debt by about 0.62. The standard deviation of Log Bank Density is 0.69, so a one standard deviation increase in the log number of bank branches within 150 miles is associated with an approximately 42.9% decline in the odds of getting debt crowdfunding compared to the median. In Columns 2 and 3, year fixed effects are used to control for intertemporal variation in the crowdfunding choice, and industry fixed effects are used to control for unobservable, time-invariant differences across industries. The estimates obtained when including county fixed effects alone, as shown in Column 1, exhibit a similar magnitude to those obtained when incorporating year and industry effects, as presented in Columns 2 and 3. In Columns 4–6, we rerun our analysis with Top Bank Density (150 miles) as the alternative measure of bank access, showing consistent results across all specifications. As per Column 6, we estimate that a firm is 9.8pp less likely to choose debt financing if it is located in a ZIP code that is in the top quartile in terms of the number of nearby bank branches.

4.5. Crowdfunding and growth

In this section of the paper, we assess whether successful crowdfunding is associated with real growth outcomes, and how these outcomes relate to the firm's stage in the financial growth cycle. As discussed in Section 1, theory does not give a clear indication of whether to expect crowdfunding to result in improved performance due to issues of information asymmetry and moral hazard. Moreover, prior empirical evidence is ambiguous on whether crowdfunding fosters growth.

To analyze the relationship between crowdfunding and firm growth, we compare firms that successfully issued crowdfunded debt or equity to a sample of matched private firms from Factset in a matched diff-in-diff setting (as in Boucly, Sraer, and Thesmar (2011)). We create a matched set of control firms from the period 2016–2021 using propensity-score matching on the following variables, measured in the year before the treated firm launches its crowdfunding campaign: SIC-2 industry, ROA, and total assets. We additionally require matched firms to have non-missing data in the year after they are matched (i.e., the counterfactual year after crowdfunding). Due to data limitations, we are only able to analyze a two-period setting: one year before crowdfunding and one year after. Consequently, we can only evaluate short-term effects associated with crowdfunding.[5]

In Table 4.7, we run matched diff-in-diff panel regressions with two-way fixed effects (firm and year) for six different outcome variables: size (log total assets), log revenue, profitability (ROA), cash holdings, book leverage, short-term leverage, and long-term leverage. We include a post-period control dummy (equal to one if the observation represents the (matched) year after crowdfunding) and a post-period and treated interaction variable, which is our primary variable of interest and captures the estimated effect associated with crowdfunding after the campaign has concluded.

We find that crowdfunding firms increase their total assets, revenue, and ROA relative to similar firms that do not issue securities via crowdfunding. More specifically, successful crowdfunding is associated with a 42% increase in size, 46% increase in revenue, and a 0.96 higher ROA (for comparison, the pre-crowdfunding sample average ROA is 2.26). Short-term leverage is expected to decrease by 0.17, consistent with a majority of the offerings in the sample being equity. In other words, compared to similar firms that do not issue crowdfunded securities, is-

[5]Our sample is limited since firms that issue securities according to Regulation CF are only required to disclose financials once prior to crowdfunding and once after the campaign succeeds (no more than 120 days after fiscal year-end). Thus, we can only observe multiple post-crowdfunding years of data for a firm if it for some reason has to extend its filing period or if it makes subsequent Form C filings in conjunction with follow-on crowdfunding campaigns.

suers appear to grow in size while simultaneously improving their performance. This suggests that any information asymmetry and moral hazard problems present during crowdfunding do not fully disincentivize entrepreneurs from putting crowdfunded capital to good use.

In Section 4, we showed that the firm's choice of debt versus equity securities is related to its stage in the financial growth cycle. Next, we investigate whether the growth effects seen above also vary by developmental stage. To do so, we include controls in Table 4.8 for the growth stage as well as a pair of three-way interaction variables: post-period times treated times growth stages two and three, respectively. This allows us to estimate the relative growth effects associated with successful crowdfunding for startups in their first, second, and third stages of development.

Table 4.8 shows large increases in size (83%), revenue (90%), and ROA (1.25) for first-stage startups that successfully crowdfund versus similar firms that do not. Relative to first-stage firms, however, second- and third-stage firms see significantly lower gains in size (-71% and -50%) and revenue (-59% and -74%), with third-stage firms additionally seeing less of an increase in ROA (-1.19). Relative to control firms without crowdfunding, only second-stage firms see gains in revenue (90%–59%=31%, significant at the 5% level) and profitability (1.25–0.21=1.04, significant at the 10% level). In contrast, third-stage firms that successfully crowdfund do not see significant gains in size, revenue, or profitability. In other words, the positive real economic effects associated with crowdfunding appear related to the firm's developmental stage, with startups that have yet to become profitable seeing significant operating gains while profitable, more mature, firms do not show signs of improvement.

Our findings may provide new context as to why prior empirical studies yield mixed predictions regarding the relationship between crowdfunding and growth. In particular, Eldridge, Nisar, and Torchia (2021) finds a positive relationship between equity crowdfunding and ROA for UK firms, while Havrylchyk and Mahdavi Ardekani (2020) do not observe any relationship between debt crowdfunding and sales growth or profitability for a sample of French firms. We document that both the firm's choice of security type — debt versus equity — and post-issuance gains in revenue and profitability are closely related to the firm's stage in the financial growth cycle.

4.6. Conclusion

Regulation CF of the JOBS Act allows small businesses in the US to offer crowdfunded debt and equity securities to individual investors. In this paper, we raise several questions regarding this recent source of startup capital: Which types of firms choose to issue crowdfunded debt, and which choose equity? How does this decision relate to the firm's stage in the financial growth cycle and access to bank lending? Is successful crowdfunding associated with realized improvements in firm size and profitability?

We start by examining the factors associated with a firm's choice between debt and equity crowdfunding. We find that larger, less profitable, and more levered firms are less likely to select debt when issuing securities via crowdfunding. We also find that the capital structure of crowdfunded firms tends to follow a growth cycle pattern. Specifically, early-stage startups are more likely than late-stage startups to finance their growth through equity crowdfunding. As firms develop, they tend to rely more on debt-based crowdfunding, potentially because improved financial stability and creditworthiness make debt financing less costly.

Next, we investigate how the availability of traditional bank financing is related to the firm's choice of crowdfunding security type. We find evidence consistent with debt crowdfunding serving as a substitute for bank lending. We show that firms located in areas with higher house prices (proxying for access to home equity, a frequent source of funding for startups) and a higher number of bank branches (proxying for access to bank loans) are more likely to issue crowdfunded equity.

To conclude our analysis, we investigate whether successful securities crowdfunding is associated with realized increases in firm size and performance. We compare firms that successfully issued crowdfunded debt or equity to a sample of matched private firms from Factset. We find that crowdfunding firms increase their total assets, revenue, and ROA relative to the control sample. This difference is largest for first-stage firms, with the relationship weakening as firms mature. While the positive association between crowdfunding and ROA is positive and significant for both first- and second-stage firms, it is insignificant for third-stage firms. Our results suggest that crowdfunding can improve operational performance for firms that are not yet profitable but has a negligible impact on more mature, profitable, firms.

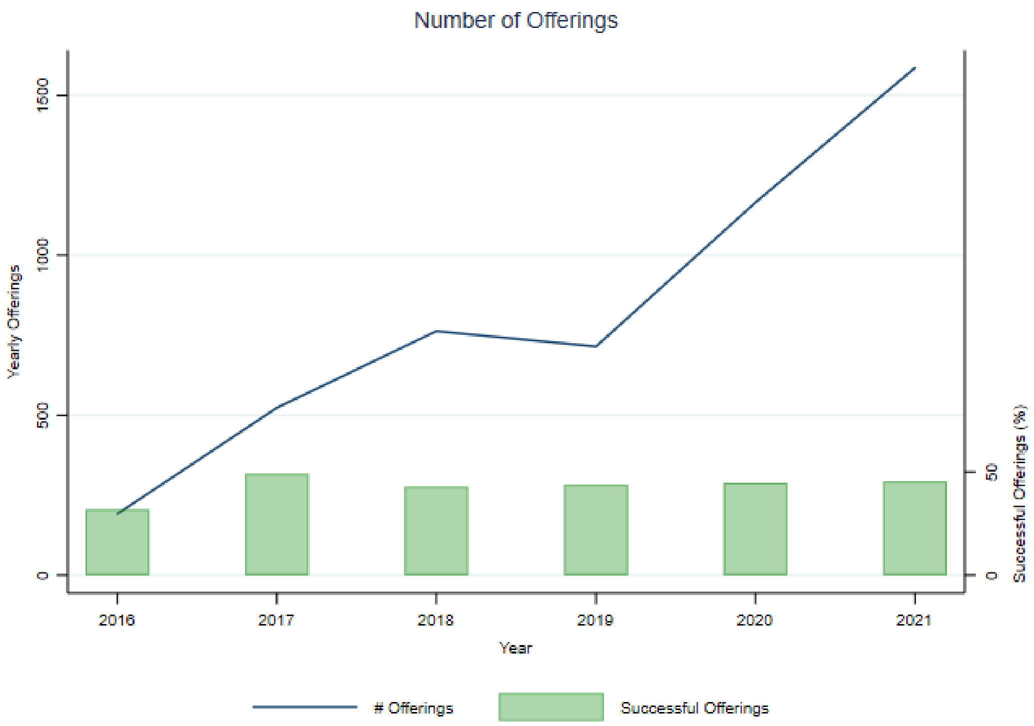

Fig. 4.1 Number of offerings and successful offerings over time. These figures show the number of offerings and successful offering from 2016 to 2021. Data comes from EDGAR.

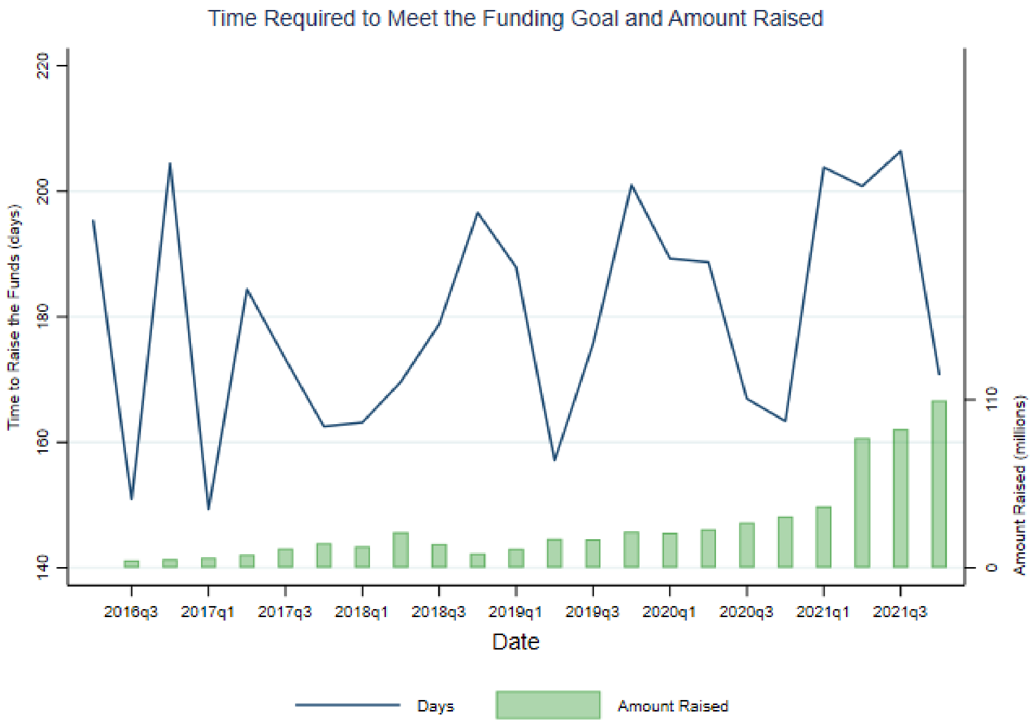

Fig. 4.2 Time required to meet the funding goal and total amount raised. These figures show respectively the total amount raised through crowdfunding (in millions USD) and the time required to raise the funds (in days). Data comes from EDGAR.

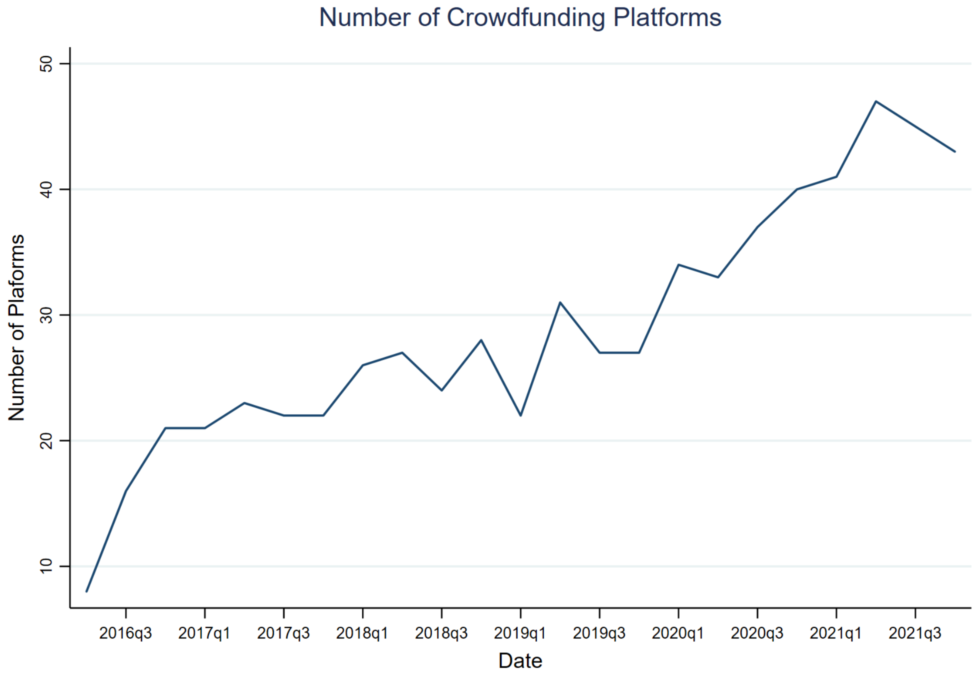

Fig. 4.3 Number of crowdfunding platforms. This figure shows the evolution of the total number crowdfunding from 2016 through 2021.

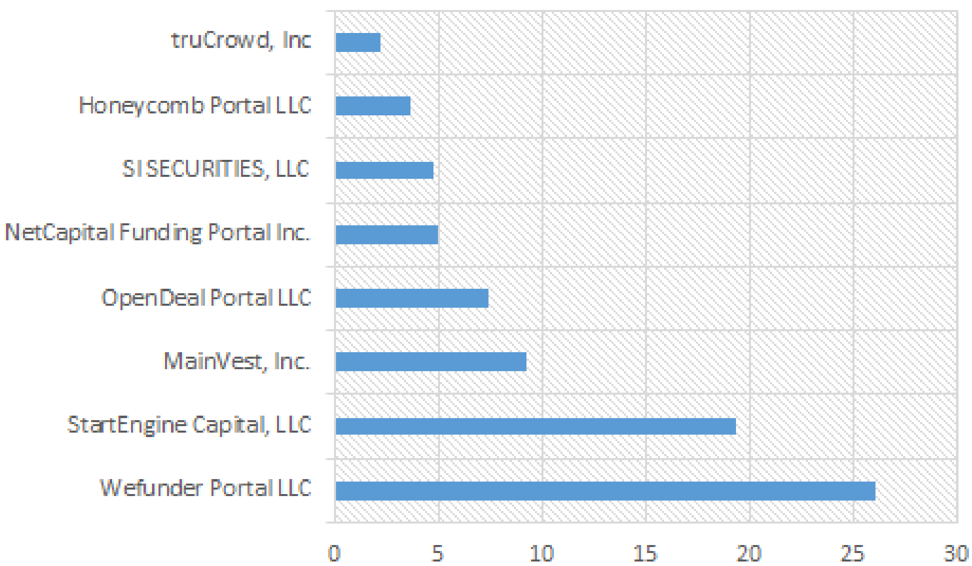

Fig. 4.4 Most popular crowdfunding platforms. This figure shows the percentage of the offerings managed by the most eight most popular crowdfunding portals. Data come from EDGAR.

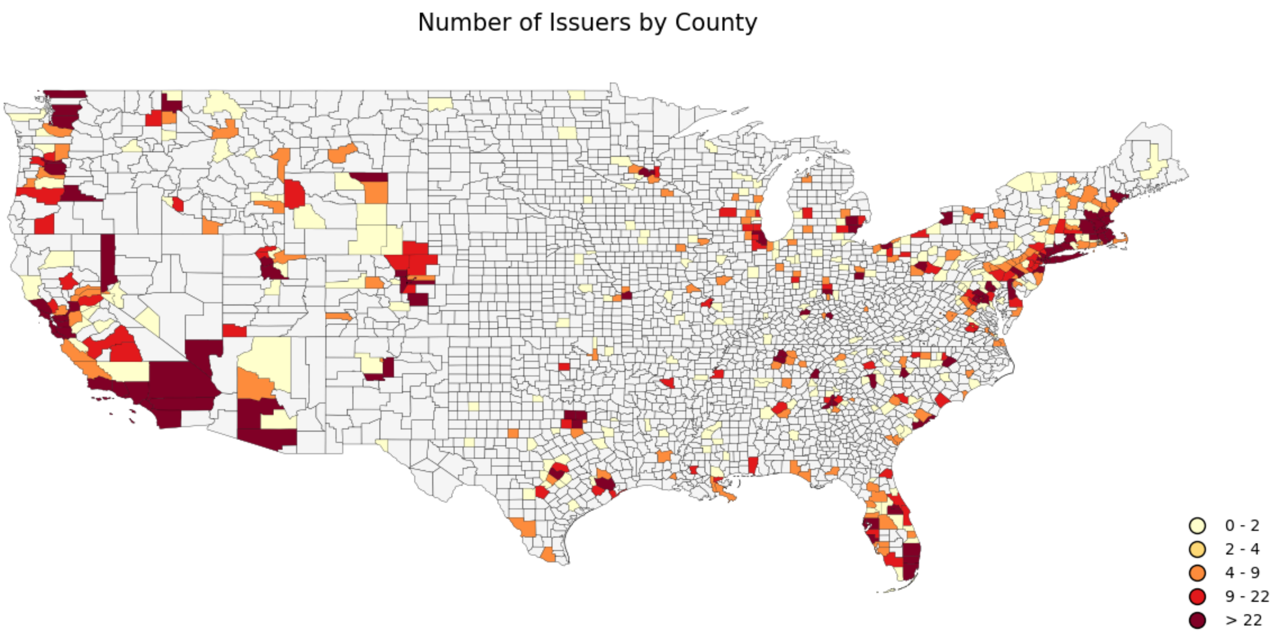

Fig. 4.5 **Crowdfunding geography.** This figure shows the country-level graph of the numbers of crowdfunding offerings across US Counties. Colors correspond to bins of the number of offerings. Data come from EDGAR.

Table 4.1 **Summary Statistics** The table presents descriptive statistics for financial variables (Panel A), crowdfunding variables (Panel B), and macro variables (Panel C). The sample covers 2,052 US crowdfunded firms from June 2016 through December 2021. We require non-zero total assets and winsorize data at (2,98) level. All variables are defined in the Appendix (Table 4.A.1). Total Assets are in millions of dollars. Columns 4, 5 and 6, 7 show the subsamples of debt-based crowdfunding (CF) and equity-based CF, respectively. The p-value in column 9 is the significance of a t-test for the difference in mean between debt and equity crowdfunding. Data sources: EDGAR, FactSet, Board of Governors of the Federal Reserve System, IPUMS National Historical Geographic Information System.

	Full Sample (N = 2052)			Debt-based CF (N = 355)		Equity-based CF (N = 1657)		Difference	p-value of
	N	Mean	Median	Mean	Median	Mean	Median	in mean	difference
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Firm Characteristics									
Total Assets	2052	708,164	103,416	1,070,204	65,549	632,428	113,741	437,776	0.236
Profitability	2052	2.36	0.35	3.75	1.33	2.07	0.25	1.68	0.000
Size	2052	11.28	11.55	11.02	11.09	11.33	11.64	-0.31	0.018
Cash holdings	2052	0.46	0.36	0.43	0.28	0.47	0.38	-0.03	0.135
Book Leverage	2052	5.07	0.92	3.35	0.85	5.43	0.94	-2.08	0.017
LT Leverage	2052	2.51	0.09	1.59	0.02	2.71	0.10	-1.11	0.019
ST Leverage	2052	1.51	0.18	1.21	0.15	1.57	0.18	-0.36	0.144
Log (Sales)	2052	11.61	11.87	11.56	11.81	11.63	11.88	-0.07	0.680
Age	2052	2.67	1.00	3.23	2.00	2.55	1.00	-0.68	0.004
Financial Growth Cycle	2052	1.86	2.00	2.07	2.00	1.81	2.00	-0.26	0.000
Log (Employees)	2052	8.98	4.00	6.96	4.00	9.43	4.00	-2.48	0.316
Panel B: Crowdfunding									
Amount Offered	2052	63631	25000	62734	25000	63834	25000	-1100	0.862
Price Security	2052	146	1	487	1	92	1	395	0.012
Type of Security	2052	0.17	0.00						
Success	2052	0.37	0.00	0.37	0.00	0.37	0.00	0.00	0.950
Previous Institutional Funding	2052	0.25	0.00	0.14	0.00	0.27	0.00	-0.12	0.000
Panel C: Macro variables									
Bank Density (150 miles)	2001	7.500	7.550	7.606	7.819	7.478	7.539	0.13	0.003
Top Bank	2001	0.25	0.00	0.33	0.00	0.23	0.00	0.09	0.001
Total population	2001	10.15	10.28	10.09	10.27	10.17	10.28	-0.08	0.130
Median Income	2001	82.74	78.07	78.80	72.16	83.58	79.27	-4.78	0.030
Frac. White	2001	21.82	20.02	21.35	18.79	21.91	20.04	-0.56	0.507
Num. of Establishment	2001	47.80	33.00	40.53	31.00	49.35	34.00	-8.82	0.007

Table 4.2 **Industry Distribution of Sample Crowdfunded Firms and Financing Choice** The table presents the distribution of sample firms based on their Standard Industrial Classification (SIC) 2-digit industry code, sorted by frequency. It also shows the number and percentage of firms that opt for debt-based crowdfunding (CF) and equity-based crowdfunding within each industry category. The sample contains 2,052 US crowdfunding campaigns, 2016–2021. All variables are defined in the Appendix (Table 4.A.1).

		All firms		Debt-based CF		Equity-based CF	
SIC2	Industry	Num.	Percent	Num.	Percent	Num.	Percent
73	Business Services	384	18.71	54	15.21	330	19.45
20	Food and Kindred Products	199	9.7	62	17.46	137	8.07
58	Eating and Drinking Places	111	5.41	42	11.83	69	4.07
87	Engineering, Accounting, Research, and Management Services	93	4.53	18	5.07	75	4.42
59	Miscellaneous Retail	87	4.24	14	3.94	73	4.3
51	Wholesale Trade - Nondurable Goods	80	3.9	15	4.23	65	3.83
79	Amusement and Recreation Services	76	3.7	11	3.1	65	3.83
28	Chemicals and Allied Products	56	2.73	7	1.97	49	2.89
54	Food Stores	50	2.44	15	4.23	35	2.06
80	Health Services	50	2.44	5	1.41	45	2.65
50	Wholesale Trade - Durable Goods	49	2.39	4	1.13	45	2.65
38	Measuring, Photographic, Medical, & Optical Goods, & Clocks	48	2.34	4	1.13	44	2.59
36	Electronic & Other Electrical Equipment & Components	47	2.29	2	0.56	45	2.65
72	Personal Services	46	2.24	8	2.25	38	2.24
48	Communications	42	2.05	5	1.41	37	2.18
35	Industrial and Commercial Machinery and Computer Equipment	38	1.85	3	0.85	35	2.06
82	Educational Services	38	1.85	7	1.97	31	1.83
27	Printing, Publishing and Allied Industries	30	1.46	2	0.56	28	1.65
78	Motion Pictures	30	1.46	2	0.56	28	1.65
37	Transportation Equipment	29	1.41	1	0.28	28	1.65
56	Apparel and Accessory Stores	28	1.36	6	1.69	22	1.3
39	Miscellaneous Manufacturing Industries	27	1.32	3	0.85	24	1.41
65	Real Estate	27	1.32	5	1.41	22	1.3
61	Nondepository Credit Institutions	26	1.27	3	0.85	23	1.36
62	Security & Commodity Brokers, Dealers, Exchanges & Services	24	1.17	5	1.41	19	1.12
67	Holding and Other Investment Offices	23	1.12	2	0.56	21	1.24
83	Social Services	23	1.12	5	1.41	18	1.06
47	Transportation Services	22	1.07	4	1.13	18	1.06
49	Electric, Gas and Sanitary Services	18	0.88	2	0.56	16	0.94
75	Automotive Repair, Services and Parking	17	0.83	4	1.13	13	0.77
89	Services, Not Elsewhere Classified	15	0.73	2	0.56	13	0.77
86	Membership Organizations	13	0.63	3	0.85	10	0.59
1	Agricultural Production - Crops	12	0.58	5	1.41	7	0.41
23	Apparel, Finished Products from Fabrics & Similar Materials	12	0.58	3	0.85	9	0.53
31	Leather and Leather Products	12	0.58	1	0.28	11	0.65
55	Automotive Dealers and Gasoline Service Stations	12	0.58	0	0	12	0.71
34	Fabricated Metal Products	11	0.54	0	0	11	0.65
15	Construction - General Contractors & Operative Builders	10	0.49	5	1.41	5	0.29
42	Motor Freight Transportation	10	0.49	1	0.28	9	0.53

Table 4.3 Financing Choice and Firm Characteristics The table presents the relationship between firm characteristics and the choice of security type in crowdfunding campaigns. The dependent variable is a dummy that takes the value of 1 when the issued security is in the form of debt, and 0 otherwise. Columns (1), (2), and (3) display the estimated coefficients for the full sample. Columns (4) and (5) present results for successful campaigns, while columns (6) and (7) report coefficients for failed campaigns. All variables are defined in the Appendix (Table 4.A.1). Firm-level variables are lagged by one year. The sample contains 2,052 US crowdfunding campaigns, 2016–2021. T-statistics are in parentheses and standard errors are clustered at the industry level. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

	Full Sample			Successful CF		Failed CF	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Profitability	0.009***	0.009***	0.008***	0.008**	0.007**	0.012***	0.010***
	(3.60)	(3.71)	(3.38)	(2.48)	(2.25)	(4.46)	(3.69)
Size	-0.013***	-0.012***	-0.011**	-0.006	-0.004	-0.022**	-0.022**
	(3.03)	(2.96)	(2.32)	(1.24)	(0.71)	(2.37)	(2.47)
Cash holdings	-0.056	-0.057	-0.027	-0.016	0.010	-0.113*	-0.082*
	(1.47)	(1.53)	(0.92)	(0.50)	(0.32)	(1.94)	(1.90)
LT Leverage	-0.003***	-0.003***	-0.003**	-0.003**	-0.002*	-0.003***	-0.003*
	(2.85)	(2.85)	(2.37)	(2.28)	(1.80)	(2.75)	(1.73)
ST Leverage	-0.005**	-0.004**	-0.003*	-0.002	-0.000	-0.010***	-0.008**
	(2.41)	(2.24)	(1.83)	(0.72)	(0.20)	(2.79)	(2.38)
Year FE		Y	Y	Y	Y	Y	Y
Industry FE			Y		Y		Y
Observations	2,052	2,052	2,045	1,292	1,286	760	741
Adjusted R-squared	0.024	0.025	0.057	0.025	0.049	0.041	0.084

Table 4.4 **Financing Choice and Growth Stage** The table presents the relationship between the stage of a firm's financial growth and the choice of security type in crowdfunding campaigns. The dependent variable is a dummy that takes the value of 1 when the issued security is in the form of debt, and 0 otherwise. Columns (1), (2), and (3) display the estimated coefficients for the full sample. Columns (4) and (5) present results for successful campaigns, while columns (6) and (7) report coefficients for failed campaigns. We categorize firms into three stages of the financial growth cycle: pre-revenue (Growth Stage 1), positive revenue but not yet profitable (Growth Stage 2), and profitable with positive revenue and net income (Growth Stage 3). All variables are defined in the Appendix (Table 4.A.1). Firm-level variables are lagged by one year. The sample contains 2,052 US crowdfunding campaigns, 2016–2021. T-statistics are in parentheses and standard errors are clustered at the industry level. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

	Full Sample			Successful CF		Failed CF	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Growth Stage 2	0.063***	0.065***	0.046*	0.092***	0.076**	0.022	0.013
	(3.69)	(3.15)	(1.97)	(3.39)	(2.44)	(0.82)	(0.38)
Growth Stage 3	0.179***	0.153***	0.133***	0.146***	0.130***	0.156***	0.122**
	(4.88)	(4.38)	(3.63)	(3.26)	(2.80)	(4.24)	(2.64)
Profitability		0.005*	0.004	0.003	0.003	0.007***	0.007**
		(1.80)	(1.62)	(0.95)	(0.87)	(2.67)	(2.46)
Size		-0.018***	-0.015***	-0.013**	-0.010	-0.024**	-0.024***
		(3.92)	(3.28)	(2.42)	(1.64)	(2.46)	(2.79)
Cash holdings		-0.041	-0.015	0.003	0.025	-0.097	-0.071
		(1.17)	(0.50)	(0.09)	(0.84)	(1.65)	(1.59)
LT Leverage		-0.003**	-0.002**	-0.003**	-0.002*	-0.003**	-0.002
		(2.61)	(2.14)	(2.14)	(1.69)	(2.55)	(1.65)
ST Leverage		-0.004*	-0.003	-0.001	-0.000	-0.009**	-0.007**
		(1.92)	(1.55)	(0.54)	(0.05)	(2.39)	(2.11)
Year FE		Y	Y	Y	Y	Y	Y
Industry FE			Y		Y		Y
Observations	2,032	2,032	2,025	1,280	1,274	752	733
Adjusted R-squared	0.023	0.037	0.064	0.037	0.056	0.054	0.092

Table 4.5 Housing Price Changes and Financing Choice of Crowdfunding The table presents the relationship between house prices and the choice of security type in crowdfunding campaigns. The dependent variable is a dummy that takes the value of 1 when the issued security is in the form of debt, and 0 otherwise. All variables are defined in the Appendix (Table 4.A.1). Firm-level variables and HPI are lagged by one year. HPI and the macro controls are at the ZIP code level. The sample contains 2,052 US crowdfunding campaigns, 2016–2021. T-statistics are in parentheses and standard errors are clustered at the industry level. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Variables	(1)	(2)	(3)	(4)
log HPI	-0.049***	-0.052***	-0.040**	-0.041*
	(2.65)	(2.68)	(2.13)	(1.92)
log Med. Inc		0.004	0.001	0.015
		(0.13)	(0.02)	(0.44)
log Population		0.009	0.005	0.002
		(0.40)	(0.20)	(0.08)
Establishments Per Cap.		-0.002	-0.002	-0.002
		(0.30)	(0.36)	(0.28)
Firm Controls	Y	Y	Y	Y
County FE	Y	Y	Y	Y
Year FE			Y	Y
Industry FE				Y
Observations	1320	1180	1180	1166

Table 4.6 Bank-lending Availability and Crowdfunding Choice The table reports results from the bank-lending availability and the choice of security type in crowdfunding campaigns regression estimations. The dependent variable is a dummy that takes the value of 1 when the issued security is in the form of debt, and 0 otherwise. All variables are defined in the Appendix (Table 4.A.1). Firm-level variables are lagged by one year. The sample contains 2,052 US crowdfunding campaigns, 2016–2021. T-statistics are in parentheses and standard errors are clustered at the industry level. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Variables	(1)	(2)	(3)	(5)	(6)	(8)
Log Bank Density (150 miles)	-0.622**	-0.588**	-0.551*			
	(2.41)	(2.27)	(1.88)			
Top Bank Density (150 miles)				-0.114***	-0.134***	-0.098*
				(2.96)	(3.47)	(1.85)
Log Med. Inc	0.000	0.000	0.000	0.000	0.000	0.000
	(0.32)	(0.41)	(0.39)	(0.31)	(0.40)	(0.39)
Frac. White	-0.036	-0.039	-0.023	-0.031	-0.034	-0.019
	(0.63)	(0.70)	(0.39)	(0.55)	(0.62)	(0.33)
Log Population	0.001	0.001	0.001	0.001	0.001	0.001
	(1.38)	(1.41)	(1.12)	(1.32)	(1.35)	(1.07)
Establishments Per Cap.	-0.000	-0.000*	-0.000*	-0.000*	-0.000*	-0.000*
	(1.67)	(1.71)	(1.70)	(1.78)	(1.82)	(1.78)
Firm Controls	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
Year FE		Y	Y		Y	Y
Industry FE			Y			Y
Observations	1,826	1,826	1,826	1,826	1,826	1,826
Adjusted R-squared	0.141	0.142	0.152	0.139	0.141	0.150

Table 4.7 Institutional Investors and Financing Choice The table provides regression results for the relationship between institutional funding and the choice of security type in crowdfunding campaigns. Columns (1), (2), and (3) display the estimated coefficients for the full sample. Columns (4) and (5) present results for successful campaigns, while columns (6) and (7) report coefficients for failed campaigns. The dependent variable is a dummy that takes the value of 1 when the issued security is in the form of debt, and 0 otherwise. All variables are defined in the Appendix (Table 4.A.1). Firm-level variables are lagged by one year. The sample contains 2,052 US crowdfunding campaigns, 2016-2021. T-statistics are in parentheses and standard errors are clustered at the industry level. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

	Full Sample			Successful CF		Failed CF	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Previous Institutional Funding	-0.094***	-0.075***	-0.065***	-0.059**	-0.040	-0.102***	-0.088**
	(5.03)	(4.07)	(3.95)	(2.14)	(1.51)	(3.01)	(2.48)
Profitability		0.009***	0.008***	0.008**	0.007**	0.011***	0.010***
		(3.66)	(3.35)	(2.41)	(2.23)	(4.23)	(3.47)
Size		-0.008*	-0.007	-0.003	-0.002	-0.015*	-0.016*
		(1.76)	(1.44)	(0.62)	(0.37)	(1.79)	(1.94)
Cash holdings		-0.046	-0.018	-0.009	0.014	-0.095*	-0.066
		(1.26)	(0.64)	(0.29)	(0.46)	(1.71)	(1.56)
LT Leverage		-0.003***	-0.003**	-0.003**	-0.002*	-0.003***	-0.003*
		(2.84)	(2.41)	(2.24)	(1.80)	(2.96)	(1.92)
ST Leverage		-0.003*	-0.003	-0.001	0.000	-0.009***	-0.008**
		(1.76)	(1.45)	(0.31)	(0.08)	(2.89)	(2.50)
Year FE		Y	Y	Y	Y	Y	Y
Industry FE			Y		Y		Y
Observations	2,052	2,052	2,045	1,292	1,286	760	741
Adjusted R-squared	0.011	0.031	0.061	0.029	0.050	0.053	0.092

Table 4.8 Crowdfunding and Growth The table presents results from the regression estimation of crowdfunding and growth. Post is a dummy variable that takes a value of 1 after the crowdfunding campaign, and 0 otherwise. Treated is a dummy variable that takes a value of 1 if the firm successfully concluded a crowdfunding campaign, and 0 otherwise. All variables are defined in the Appendix (Table 4.A.1). Firm-level variables are lagged by one year. The sample contains 349 US crowdfunding firms and their matched controls, 2016-2021. Data frequency is yearly. T-statistics are in parentheses and standard errors are clustered at the industry level. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

	(1) Size	(2) Log Revenue	(3) Profitability	(4) Cash holdings	(5) Book Leverage	(6) ST Leverage	(7) LT Leverage
Post	0.064	-0.065	-0.476	0.002	-0.861**	0.008	0.007
	(0.38)	(0.51)	(0.74)	(0.06)	(2.50)	(0.42)	(0.17)
Post x Treated	0.424***	0.464***	0.964*	0.044	0.274	-0.168***	-0.141
	(2.67)	(4.33)	(1.73)	(1.56)	(0.71)	(2.99)	(1.21)
Year FE	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y
Observations	1,359	1,113	1,352	1,349	1,241	1,363	1,241
Adjusted R-squared	0.700	0.871	0.673	0.693	0.494	0.511	0.619

Table 4.9 Crowdfunding, Growth, and Financial Growth Cycle The table presents the relationship between crowdfunding, growth, and the financial growth cycle. Post is a dummy variable that takes a value of 1 after the crowdfunding campaign, and 0 otherwise. Treated is a dummy variable that takes a value of 1 if the firm successfully concluded a crowdfunding campaign, and 0 otherwise. We categorize firms into three stages of the financial growth cycle: pre-revenue (Growth Stage 1), positive revenue but not yet profitable (Growth Stage 2), and profitable with positive revenue and net income (Growth Stage 3). All variables are defined in the Appendix (Table 4.A.1). Firm-level variables are lagged by one year. The sample contains 349 US crowdfunding firms and their matched controls, 2016-2021. Data frequency is yearly. T-statistics are in parentheses and standard errors are clustered at the industry level. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

	(1) Size	(2) Revenue	(3) Profitability	(4) Cash holdings	(5) Book Leverage	(6) ST Leverage	(7) LT Leverage
Post	-0.027	-0.079	-0.526	0.019	-0.361	0.005	0.009
	(0.17)	(0.66)	(0.82)	(0.57)	(1.21)	(0.24)	(0.23)
Post x Treated	0.829***	0.899***	1.248**	0.028	-0.468	-0.162*	-0.338*
	(4.54)	(5.43)	(2.23)	(0.81)	(1.18)	(1.93)	(1.79)
Post x Treated x Growth Stage 2	-0.705***	-0.588***	-0.212	0.023	0.214	-0.092	0.369
	(4.80)	(3.02)	(1.07)	(0.63)	(0.51)	(0.73)	(1.42)
Post x Treated x Growth Stage 3	-0.498***	-0.738***	-1.190***	-0.075	0.697*	0.221*	0.450*
	(2.70)	(4.05)	(3.02)	(1.40)	(1.82)	(1.83)	(1.87)
Growth Stage 2	0.748	-0.351**	3.525**	-0.265	0.112	0.332	-0.054
	(1.59)	(2.31)	(2.28)	(1.10)	(0.21)	(1.14)	(0.37)
Growth Stage 3	1.184**		1.662	-0.252	0.130	0.306	-0.070
	(2.53)		(0.99)	(1.04)	(0.21)	(1.04)	(0.45)
Year FE	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y
Observations	1,339	1,109	1,336	1,329	1,221	1,343	1,221
Adjusted R-squared	0.719	0.876	0.683	0.709	0.558	0.502	0.620

APPENDIX

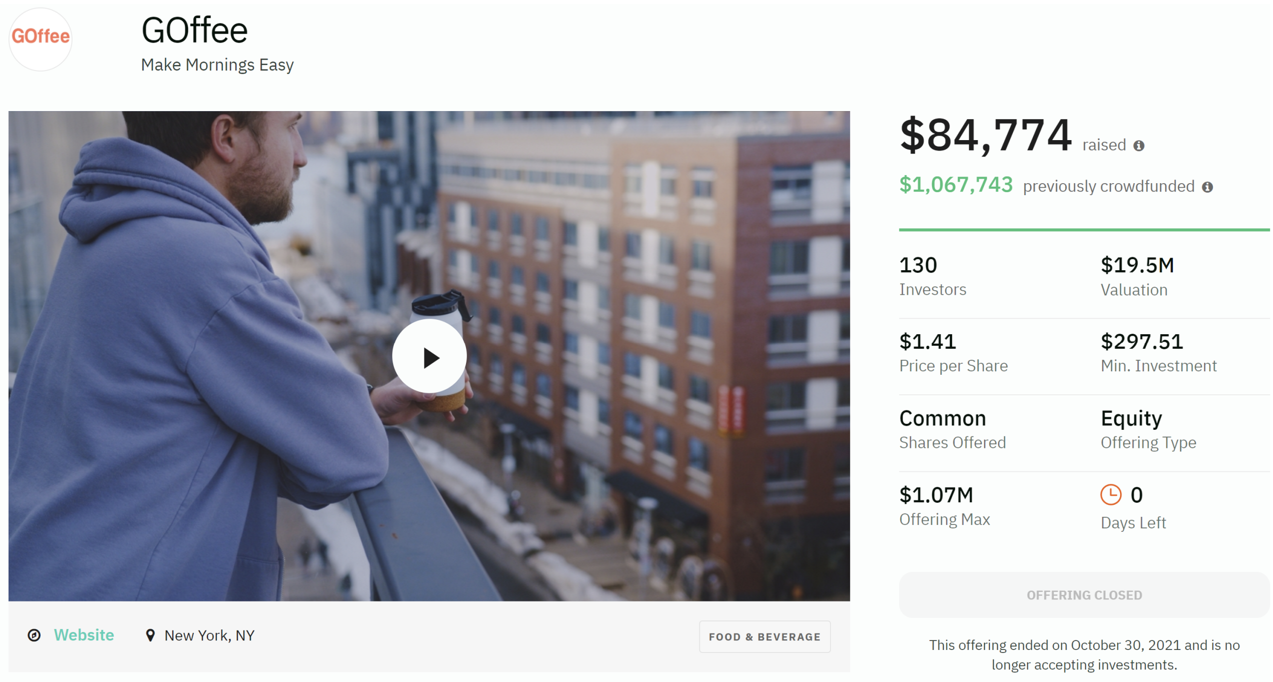

Fig. 4.A.1 Example of a crowdfunding offering. This figure shows the example of a crowdfunding offering from StartEngine.

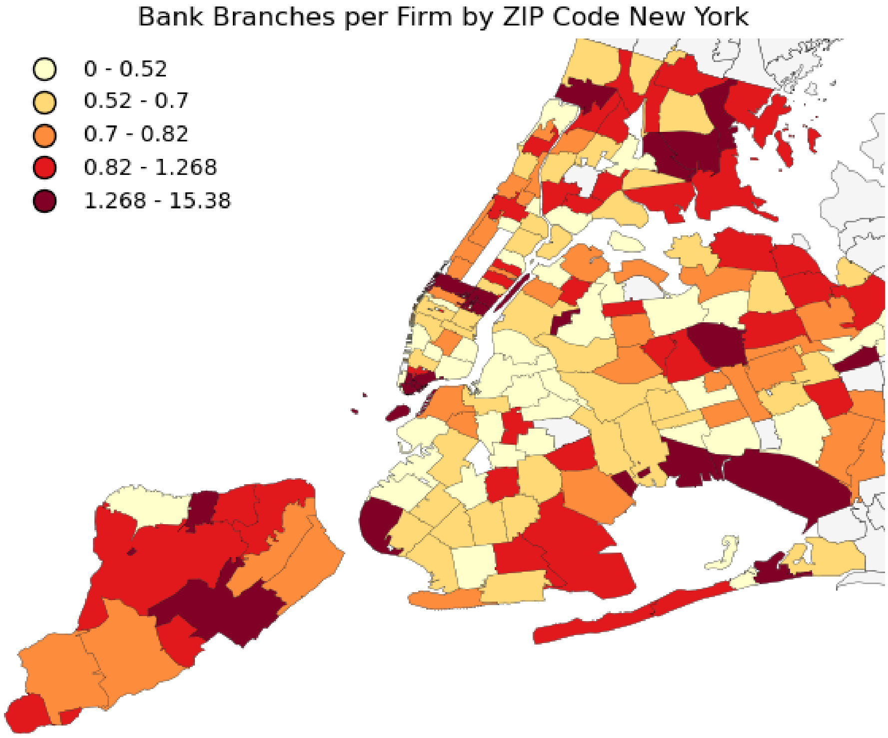

Fig. 4.A.2 **Number of bank branches New York Metropolitan Area.** This figure shows data from New York County, Bronx County, Queens County, Kings County, and Richmond County (New York Metropolitan Area) ZIP Codes. Colors correspond to bins of the number bank branches per establishment per ZIP code.

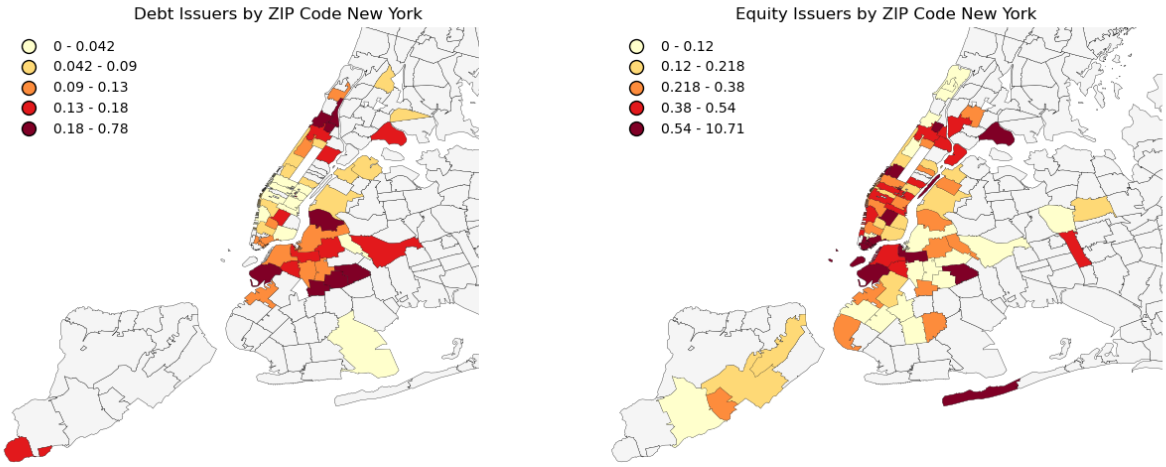

Fig. 4.A.3 Number of debt and issuers New York Metropolitan Area: This figure shows data from New York County, Bronx County, Queens County, Kings County, and Richmond County (New York Metropolitan Area) ZIP Codes. The left panel colors correspond to bins of the percentage of establishments that issued debt securities through crowdfunding. The right panel colors correspond to bins of the percentage of establishments that issued equity securities through crowdfunding.

Table 4.A.1 Variable Definition

Variables	Source	Description
A. Firm Characteristics (measured at the most recent fiscal year (t-1))		
Profitability	Edgar Form C	Revenue/Total Assets
Total Assets	Edgar Form C	Total Assets (in $ million)
Size	Edgar Form C	Natural log of total assets
Cash holdings	Edgar Form C	Cash and cash equivalents/Total Assets
Book Leverage	Edgar Form C	Total Debt/Total Assets
LT Leverage	Edgar Form C	Long-term Debt/Total Assets
ST Leverage	Edgar Form C	Short-term Debt/Total Assets
Log (Sales)	Edgar Form C	Natural log of total revenues
Age	Edgar Form C	First form C filing date - Date in corporation
Financial Growth Cycle	Edgar Form C	Growth stage = 1 if Revenue = 0 & Net Income <= 0 Growth stage = 2 if Revenue > 0 & Net Income <= 0 Growth stage = 3 if Revenue > 0 & Net Income > 0
Log (Employees)	Edgar Form C	Natural log of current employees
B. Crowdfunding		
Amount Offered	Edgar Form C	Amount offered
Price Security	Edgar Form C	Price security
Num. of Securities	Edgar Form C	Number of securities issued
Time to raise funds	Edgar Form C	First form C Filing date - Filing date form C/U (signaling the success of the crowdfunding campaign)
Interest Rate	Edgar Form C	Interest rate that the issuer pays to the intermediary
Type of Security	Edgar Form C	Dummy that takes the value of 1 when the issued security is in the form of debt, and 0 if equity. Equity definition includes common stock, preferred stock, and other securities
Success	Edgar Form C	Dummy that takes the value of 1 when firms raise the crowdfunding campaign target amount and 0 otherwise
Previous Institutional Funding	Edgar Form D	The variable takes a binary value of 1 if a firm filed Form D prior to the crowdfunding campaign, indicating that the firm received financing from Private Equity, Venture Capital, or Hedge Funds. Otherwise, it takes a value of 0 if the firm did not file Form D, indicating no such financing.
C. Macro variables		
Num. Bank Branches	FDIC Summary of Deposits Database	Number of bank branches per ZIP code
Bank Density (100 miles)	FDIC Summary of Deposits Database	Log of the total number of bank branches within 100 miles from the issuer's location
Bank Density (150 miles)	FDIC Summary of Deposits Database	Log of the total number of bank branches within 150 miles from the issuer's location
Total population	American Community Survey, 2016–2020	Total population per ZIP code
Median Income	American Community Survey, 2016–2020	Median income per ZIP code
Num. of Establishment	American Community Survey, 2016–2020	Number of establishment per ZIP code

Table 4.A.2 Financing Choice and Growth Stage (proxied by Age) The table presents the relationship between the choice of security type in crowdfunding campaigns and age. All variables are defined in the Appendix (Table 4.A.1). Firm-level variables are lagged by one year. The sample contains 2,052 US crowdfunding campaigns, 2016–2021. T-statistics are in parentheses and standard errors are clustered at the industry level. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

	Full Sample			Successful CF		Failed CF	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age	0.006*	0.006**	0.007**	0.005	0.005	0.009**	0.011***
	(1.69)	(2.07)	(2.22)	(1.46)	(1.38)	(2.33)	(2.81)
Profitability		0.009***	0.008***	0.008**	0.007**	0.011***	0.010***
		(3.67)	(3.30)	(2.40)	(2.19)	(4.56)	(3.60)
Size		-0.015***	-0.014***	-0.008**	-0.007	-0.026**	-0.027**
		(3.35)	(2.93)	(2.00)	(1.39)	(2.56)	(2.68)
Cash holdings		-0.048	-0.020	-0.006	0.019	-0.105*	-0.075*
		(1.31)	(0.68)	(0.18)	(0.59)	(1.87)	(1.81)
LT Leverage		-0.003***	-0.003**	-0.003**	-0.003**	-0.003***	-0.003*
		(3.12)	(2.51)	(2.49)	(2.03)	(2.73)	(1.74)
ST Leverage		-0.005**	-0.004*	-0.002	-0.001	-0.011***	-0.010**
		(2.29)	(1.81)	(0.80)	(0.31)	(2.88)	(2.53)
Year FE		Y	Y	Y	Y	Y	Y
Industry FE			Y		Y		Y
Observations	2,011	2,011	2,002	1,258	1,253	753	735
Adjusted R-squared	0.004	0.029	0.062	0.028	0.055	0.050	0.094

Bibliography

Abel, A., Eberly, J., 1994. A unified model of investment under uncertainty. American Economic Review 84, 1369–1384.

Agarwal, S., Hauswald, R., 2010. Distance and private information in lending. The Review of Financial Studies 23, 2757–2788.

Aghion, P., Van Reenen, J., Zingales, L., 2013. Innovation and institutional ownership. American Economic Review 103, 277–304.

Agrawal, A., Catalini, C., Goldfarb, A., 2014. Some simple economics of crowdfunding. Innovation Policy and the Economy 14, 63–97.

Agrawal, A., Catalini, C., Goldfarb, A., 2015. Crowdfunding: Geography, social networks, and the timing of investment decisions. Journal of Economics & Management Strategy 24, 253–274.

Anton, M., Ederer, F., Gine, M., Schmalz, M., 2022. Common ownership, competition, and top management incentives. Journal of Political Economy 131, 1294–355.

Anton, M., Ederer, F., Gine, M., Schmalz, M. C., 2017. Innovation: The bright side of common ownership? SSRN Electronic Journal .

Antón, M., Lin, L. X., 2019. The mutual friend: Dual holder monitoring and firm investment efficiency. The Review of Corporate Finance Studies 9, 81–115.

Appel, I. R., Gormley, T. A., Keim, D. B., 2016. Passive investors, not passive owners. Journal of Financial Economics 121, 111–141.

Appel, I. R., Gormley, T. A., Keim, D. B., 2018. Standing on the shoulders of giants: The effect of passive investors on activism. The Review of Financial Studies 32, 2720–2774.

Arikan, A., Stulz, R., 2016. Corporate acquisitions, diversification, and the firm's life cycle. Journal of Finance 71, 139–194.

Autor, D., Dorn, D., Katz, L. F., Patterson, C., Van Reenen, V., 2020. The fall of the labor share and the rise of superstar firms*. The Quarterly Journal of Economics 135, 645–709.

Ayyagari, M., Demirgüç-Kunt, A., Maksimovic, V., 2023. The Rise of Star Firms: Intangible Capital and Competition. The Review of Financial Studies .

Azar, J., Raina, S., Schmalz, M., 2021. Ultimate ownership and bank competition. Financial Management 51, 227–269.

Azar, J., Schmalz, M. C., Tecu, I., 2018a. Anticompetitive effects of common ownership. The Journal of Finance 73, 1513–1565.

Azar, J., Schmalz, M. C., Tecu, I., 2018b. Reply to: 'common ownership does not have anti-competerstitive effects in the airline industry'. SSRN Electronic Journal .

Azar, J., Vives, X., 2019. Common ownership and the secular stagnation hypothesis. AEA Papers and Proceedings 109, 322–326.

Baker, A. C., Larcker, D. F., Wang, C. C., 2022. How much should we trust staggered difference-in-differences estimates? Journal of Financial Economics 144, 370–395.

Baqaee, D. R., Farhi, E., 2019. Productivity and misallocation in general equilibrium*. The Quarterly Journal of Economics 135, 105–163.

Barkai, S., 2020. Declining labor and capital shares. The Journal of Finance 75, 2421–63.

Bates, T., Kahle, K., Stulz, R., 2009. Why do u.s. firms hold so much more cash than they used to? Journal of Finance 64, 1985–2021.

Berger, A., Udell, G., 1998. The economics of small business finance: The roles of private equity and debt markets in the financial growth cycle. Journal of Banking & Finance 22, 613–673.

Bloom, N., Schankerman, M., Van Reenen, J., 2013. Identifying technology spillovers and product market rivalry. Econometrica 81, 1347–1393.

Bloom, N., Van Reenen, J., 2007. Measuring and explaining management practices across firms and countries. The Quarterly Journal of Economics 122, 1351–1408.

Bollaert, H., Lopez-de Silanes, F., Schwienbacher, A., 2021. Fintech and access to finance. Journal of Corporate Finance 68, 101941.

Boller, L., Morton, S., 2020. Testing the theory of common stock ownership. SSRN Electronic Journal .

Bolton, P., Chen, H., Wang, N., 2011. A unified theory of Tobin's q, corporate investment, financing, and risk management. Journal of Finance 66, 1545–1578.

Borochin, P., Yang, J., Zhang, R., 2018. The effect of institutional ownership types on innovation and competition. SSRN Electronic Journal .

Boucly, Q., Sraer, D., Thesmar, D., 2011. Growth LBOs. Journal of Financial Economics 102, 432–453.

Brav, A., Malenko, A., Malenko, N., 2023. Corporate Governance Implications of the Growth in Indexing.

Brevoort, K. P., Wolken, J. D., Holmes, J. A., 2010. Distance still matters: The information revolution in small business lending and the persistent role of location, 1993-2003. FEDS Working Paper .

Bushee, B. J., 1998. The influence of institutional investors on myopic r&d investment behavior. The Accounting Review 73, 305–333.

Bushee, B. J., 2001. Do institutional investors prefer near-term earnings over long-run value? Contemporary Accounting Research 18, 207–246.

Bustamante, C., Cujean, J., Frésard, L., 2021. Knowledge cycles and corporate investment. Tech. rep.

Butticè, V., Di Pietro, F., Tenca, F., 2020. Is equity crowdfunding always good? Deal structure and the attraction of venture capital investors. Journal of Corporate Finance 65, 101773.

Carlson, M., Fisher, A., Giammarino, R., 2004. Corporate investment and asset price dynamics: Implications for the cross-section of returns. Journal of Finance 59, 2577–2603.

Cengiz, D., Dube, A., Lindner, A., Zipperer, B., 2019. The Effect of Minimum Wages on Low-Wage Jobs*. The Quarterly Journal of Economics 134, 1405–1454.

Clementi, G. L., Palazzo, B., 2019. Investment and the cross-section of equity returns. Journal of Finance 74, 281–321.

Cohen, W. M., Levinthal, D. A., 1990. Absorptive capacity: a new perspective on learning and innovation. Administrative Science Quarterly 35, 128–152.

Cole, R. A., Liang, C. Y., Zhang, R., 2020. Debt financing of small OTC firms reporting to the SEC. Available at SSRN 3679594 .

Cole, R. A., Sokolyk, T., 2018. Debt financing, survival, and growth of start-up firms. Journal of Corporate Finance 50, 609–625.

Coleman, S., 2002. Small firm use of debt: An examination of the smallest small firms. The Journal of Entrepreneurial Finance 7, 51–76.

Crouzet, N., Eberly, J., 2018. Intangibles, investment, and efficiency. AEA Papers and Proceedings 108, 426–431.

Crouzet, N., Eberly, J., 2021. Intangibles, markups, and the measurement of productivity growth. Journal of Monetary Economics 124, S92–S101.

Cumming, D., Dai, N., 2010. Local bias in venture capital investments. Journal of Empirical Finance 17, 362–380.

Cumming, D. J., Johan, S. A., Reardon, R. S., 2022. Governance and success in US equity crowdfunding. Tech. rep., CFS Working Paper Series.

Cumming, D. J., Johan, S. A., Zhang, Y., 2019. The role of due diligence in crowdfunding platforms. Journal of Banking & Finance 108, 105661.

De Loecker, D., Eeckhout, J., Unger, G., 2020a. The rise of market power and the macroeconomic implications*. The Quarterly Journal of Economics 135, 561–644.

De Loecker, J., Eeckhout, J., Unger, G., 2020b. The rise of market power and the macroeconomic implications. Quarterly Journal of Economics 135, 561–644.

Décamps, J. P., Mariotti, T., Rochet, J. C., Villeneuve, S., 2011. Free cash flow, issuance costs, and stock prices. Journal of Finance 66, 1501–1544.

DeMarzo, P., Fishman, M., He, Z., Wang, N., 2012. Dynamic agency and the q theory of investment. Journal of Finance 67, 2295–2340.

DeMarzo, P., Sannikov, Y., 2006. Optimal security design and dynamic capital structure in a continuous-time agency model. Journal of Finance 61, 2681–2724.

Demsetz, H., 1973. Industry structure, market rivalry, and public policy. The Journal of Law & Economics 16, 1–9.

Dennis, P., Gerardi, K., Schenone, C., 2022. Common ownership does not have anticompetitive effects in the airline industry. The Journal of Finance 77, 2765–2798.

Diamond, D. W., 1984. Financial intermediation and delegated monitoring. The Review of Economic Studies 51, 393–414.

Diamond, D. W., 1991. Monitoring and reputation: The choice between bank loans and directly placed debt. Journal of Political Economy 99, 689–721.

Dickinson, V., 2011. Cash flow patterns as a proxy for firm life cycle. The Accounting Review 86, 1969–1994.

Dolatabadi, I., Fracassi, C., Yang, L., 2021. Equity Crowdfunding in the US. Available at SSRN 3934662 .

Duchin, R., 2010. Cash holdings and corporate diversification. Journal of Finance 65, 955–992.

Edmans, A., Levit, D., Reilly, D., 2018. Governance under common ownership. The Review of Financial Studies 32, 2673–2719.

Eldar, O., Grennan, J., 2023. Common Venture Capital Investors and Startup Growth. The Review of Financial Studies .

Eldridge, D., Nisar, T. M., Torchia, M., 2021. What impact does equity crowdfunding have on SME innovation and growth? An empirical study. Small Business Economics 56, 105–120.

Elhauge, E., 2016. Horizontal shareholding as an antitrust violation. Harvard Law Review 129, 1267–1317.

Erel, I., Liebersohn, J., 2022. Can fintech reduce disparities in access to finance? evidence from the paycheck protection program. Journal of Financial Economics 146, 90–118.

Ewens, M., Farre-Mensa, J., 2022. Private or public equity? The evolving entrepreneurial finance landscape. Annual Review of Financial Economics 14, 271–293.

Faff, R., Kwok, W. C., Podolski, E. J., Wong, G., 2016. Do corporate policies follow a life-cycle? Journal of Banking & Finance 69, 95–107.

Fama, E. F., French, K. R., 1997. Industry costs of equity. Journal of Financial Economics 43, 153–193.

Field, L. C., Karpoff, J. M., 2002. Takeover defenses of ipo firms. The Journal of Finance 57, 1857–1889.

Foster, L., Grim, C., Haltiwanger, J., 2016. Reallocation in the great recession: Cleansing or not? Journal of Labor Economics 34, S293–S331.

Frank, M. Z., Goyal, V. K., 2009. Capital structure decisions: Which factors are reliably important? Financial Management 38, 1–37.

Goldstein, R., Ju, N., Leland, H., 2001. An EBIT-based model of dynamic capital structure. Journal of Business 74, 483–512.

Gorbenko, A. S., Strebulaev, I. A., 2010. Temporary versus permanent shocks: Explaining corporate financial policies. Review of Financial Studies 23, 2591–2647.

Grullon, G., Larkin, Y., Michaely, R., 2019. Are us industries becoming more concentrated?*. Review of Finance 23, 697–743.

Gryglewicz, S., Mancini, L., Morellec, E., Schroth, E. J., Valta, P., 2022. Understanding cash flow risk. Review of Financial Studies 35, 3922–3972.

Gryglewicz, S., Mayer, S., Morellec, E., 2020. Agency conflicts and short- versus long-termism in corporate policies. Journal of Financial Economics 136, 718–742.

Gutiérrez, G., Philippon, T., 2017. Declining competition and investment in the u.s.

Hackbarth, D., Miao, J., Morellec, E., 2006. Capital structure, credit risk, and macroeconomic conditions. Journal of Financial Economics 82, 519–550.

Hackbarth, D., Rivera, A., Wong, T., 2021. Optimal short-termism. Management Science forthcoming.

Hansen, R. G., Lott, J. R., 1996. Externalities and corporate objectives in a world with diversified shareholder/consumers. The Journal of Financial and Quantitative Analysis 31, 43.

Havrylchyk, O., Mahdavi Ardekani, A., 2020. Real effects of lending-based crowdfunding platforms on the SMEs. Available at SSRN 3717170 .

Hayashi, F., 1982a. Tobin's marginal q and average q: A neoclassical interpretation. Econometrica 50, 213.

Hayashi, F., 1982b. Tobin's marginal q and average q: A neoclassical interpretation. Econometrica 50, 215–224.

He, J. J., Huang, J., 2017. Product market competition in a world of cross-ownership: Evidence from institutional blockholdings. The Review of Financial Studies 30, 2674–2718.

He, J. J., Huang, J., Zhao, S., 2019. Internalizing governance externalities: The role of institutional cross-ownership. Journal of Financial Economics 134, 400–418.

Heckman, J., 1979. Sample selection bias as a specification error. Econometrica 47, 153–161.

Hoberg, G., Maksimovic, V., 2021. Product life cycles in corporate finance. Review of Financial Studies 35, 4249–4299.

Holmstrom, B., 1989. Agency costs and innovation. Journal of Economic Behavior Organization 12, 305–327.

Hornuf, L., Schmitt, M., Stenzhorn, E., 2017. Equity Crowdfunding in Germany and the UK: Follow-up funding and firm failure. Tech. rep., CESifo.

Hou, K., Xue, C., Zhang, L., 2015. Digesting anomalies: An investment approach. Review of Financial Studies 28, 650–705.

Ibbotson, R. G., Jaffe, J., 1975. Hot issue markets. Journal of Finance 30, 1027–1042.

Koch, A., Panayides, M., Thomas, S., 2020. Common ownership and competition in product markets. Journal of Financial Economics 139, 109–37.

Lambert, T., Ralcheva, A., Roosenboom, P., 2022. Crowdfunding Entrepreneurship: Evidence from US Counties. Available at SSRN .

Leland, H. E., 1998. Agency costs, risk management, and capital structure. Journal of Finance 53, 1213–1243.

Leland, H. E., Toft, K., 1996. Optimal capital structure, endogenous bankruptcy, and the term structure of credit spreads. Journal of Finance 51, 987–1019.

Lewellen, J., Lewellen, K., 2021. Institutional Investors and Corporate Governance: The Incentive to Be Engaged. The Journal of Finance 77, 213–264.

Lewellen, K., Lowry, M., 2021. Does common ownership really increase firm coordination? Journal of Financial Economics 141, 322–344.

Li, X., Liu, T., Taylor, L. A., 2023. Common ownership and innovation efficiency. Journal of Financial Economics 147, 475–497.

Liu, L. X., Whited, T. M., Zhang, L., 2015. Investment-based expected stock returns. Journal of Political Economy 117, 1105–1139.

Loderer, C., Stulz, R., Waelchli, U., 2017. Firm rigidities and the decline in growth ppportunities. Management Science 63, 3000–3020.

Loughran, T., Ritter, J., 2004. Why has ipo underpricing changed over time? Financial Management 33, 5–37.

López, A., Vives, X., 2019. Overlapping ownership, r&d spillovers, and antitrust policy. Journal of Political Economy 127, 2394–2437.

Manso, G., 2011. Motivating innovation. Journal of Finance 66, 1823–1860.

Manson, S., Schroeder, J., Riper, D. V., Kugler, T., Ruggles, S., 2022. Ipums national historical geographic information system: Version 17.0 [dataset]. Minneapolis, MN: Ipums.

McCahery, J. A., Sautner, Z., Starks, L. T., 2016. Behind the scenes: The corporate governance preferences of institutional investors. The Journal of Finance 71, 2905–2932.

Mochkabadi, K., Volkmann, C. K., 2020. Equity crowdfunding: A systematic review of the literature. Small Business Economics 54, 75–118.

Myers, S. C., Majluf, N. S., 1984. Corporate financing and investment decisions when firms have information that investors do not have. Journal of financial economics 13, 187–221.

Nanda, R., Phillips, G. M., 2022. Small firm financing frictions: How salient are they and what are their real effects? Review and perspectives for new research. Review and Perspectives for New Research .

Nguyen, H.-L. Q., 2019. Are credit markets still local? Evidence from bank branch closings. American Economic Journal: Applied Economics 11, 1–32.

Olley, S. G., Pakes, A., 1996. The dynamics of productivity in the telecommunications equipment industry. Econometrica 64, 1263.

Peters, R. H., Taylor, L. A., 2017a. Intangible capital and the investment q relation. Journal of Financial Economics 123, 251–272.

Peters, R. H., Taylor, L. A., 2017b. Intangible capital and the investment-q relation. Journal of Financial Economics 123, 251–272.

Rashidi Ranjbar, H., 2022. Return-based Crowdfunding and Entrepreneurship. Available at SSRN .

Richardson, S., 2006. Over-investment of free cash flow. Review of Accounting Studies 11, 159–189.

Robb, A. M., Robinson, D. T., 2012. The capital structure decisions of new firms. The Review of Financial Studies 27, 153–179.

Rock, E. B., Kahan, M., 2018. Index Funds and Corporate Governance: Let Shareholders be Shareholders. SSRN Electronic Journal .

Shumway, R., Stoffer, D., 1982. An approach to time series smoothing and forecasting using the em algorithm. Journal of Time Series Analysis 3, 253–264.

Strebulaev, I. A., 2007. Do tests of capital structure theory mean what they say? Journal of Finance 62, 1747–1787.

Stuart, T., Sorenson, O., 2003. The geography of opportunity: Spatial heterogeneity in founding rates and the performance of biotechnology firms. Research Policy 32, 229–253.

Traina, J., 2018. Is aggregate market power increasing? production trends using financial statements. SSRN Electronic Journal .

Vives, X., 2019. Common ownership, market power, and innovation. International Journal of Industrial Organization 70, 102528.

Vulkan, N., Åstebro, T., Sierra, M. F., 2016. Equity crowdfunding: A new phenomena. Journal of Business Venturing Insights 5, 37–49.

Zhang, L., 2017. The investment capm. European Financial Management 23, 545–603.