How do firms choose between growth and efficiency?*

Laurent Frésard†
Swiss Finance Institute
USI Lugano

Loriano Mancini‡
Swiss Finance Institute
USI Lugano

Enrique Schroth§
EDHEC Business School
CEPR

Davide Sinno¶
Swiss Finance Institute
USI Lugano

November 18, 2022

Abstract

We estimate the unobservable effort that firms put into boosting their efficiency. Identification comes from a model in which firms accumulate capital but also choose a flow of effort that controls efficiency period by period. Model estimates show that, for all cohorts and industries, young firms choose relatively more growth and old firms choose more efficiency. Amongst young firms, higher capital growth predicts higher markups in the long-term, but increases the risk of not surviving into maturity. Our model estimates help explain the priced firms' exposures to the profitability and investment risk factors of the investment CAPM.

Keywords: Efficiency, growth, short-term effort, investment, estimation.
JEL Classification Numbers: D25, G31, O40.

*Laurent Frésard, Loriano Mancini and Davide Sinno gratefully acknowledge the financial support from the Swiss Finance Institute and the Swiss National Science Foundation under the SNF grant 100018_189191.

†Laurent Frésard is with the Institute of Finance, USI Lugano, Via Giuseppe Buffi 13, CH-6900 Lugano, Switzerland. E-mail: laurent.fresard@usi.ch.

‡Loriano Mancini is with the Institute of Finance, USI Lugano, Via Giuseppe Buffi 13, CH-6900 Lugano, Switzerland. E-mail: loriano.mancini@usi.ch.

§Enrique Schroth is with EDHEC Business School, 393, Promenade des Anglais, 06202 Nice Cedex 3, France. E-mail: enrique.schroth@edhec.edu.

¶Davide Sinno is with the Institute of Finance, USI Lugano, Via Giuseppe Buffi 13, CH-6900 Lugano, Switzerland. E-mail: davide.sinno@usi.ch.

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 growth and efficiency, whether there is an optimal balance between both strategies, and if so, at what stage of their life should firms favor one over the other. This limitation arises mainly because, unlike the inputs to growth, the policies towards achieving a given level of efficiency are *not* observable or difficult to quantify. Hence, researchers do not consider efficiency as something firms choose, but treat it as exogenous. For instance, in models following the neoclassical tradition, growth results from firms' choice of productive inputs (e.g., physical and intangible capital, or labor), for a given level of efficiency modelled via an exogenous productivity process. In this framework, the level of firms' efficiency is therefore treated as a "residual".

In this paper, we consider that efficiency is not a residual but a choice, and we estimate the unobservable effort that firms put into boosting their efficiency. To do so, we develop a model in which a firm chooses capital and labor inputs *jointly* with the level of productive efficiency, and estimate this efficiency level from the data. In the model, a firm employs capital and labor to produce earnings, but can also choose the level of effort to make these inputs more productive period by period. We view this choice as a problem of short-term effort provision, and specifically posit that the effects of the firm's efficiency-boosting effort on earnings only last one period. Hence, unlike the choice of capital and labor, the effort to increase productive efficiency does not affect the

[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.

firm's growth rate. In the model, short-term effort modifies output without any change in capital and labor. By choosing its short-term effort, the firm directly influences its level of productivity.

Our main contribution is to identify the unobservable level of efficiency-boosting short-term effort from the data. The model's solution describes the firm's optimal capital investment, labor growth and short-term effort policies in closed form, as a result of the trade-offs between the marginal benefits and costs of adjusting each factor or exerting efficiency-boosting effort. Higher levels of short-term 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, short-term 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 steady-state optimal short-term effort can be identified as a function of its *observed* investment and labor growth policies and the time series of 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 estimate the model (14 parameters) at a very granular level by forming 1,346 distinct groups composed of ten homogeneous firms (exposed to similar shocks). This granular estimation enables us to describe the optimal allocations of investment, hiring, and short-term effort across cohorts of firms within industries and over time.

We find a large heterogeneity in the chosen level of productive efficiency across firms. The heterogeneity is not only in the level of short-term effort but also in the ratio of short-term effort to investment, which captures the relative importance of efficiency over growth. That is, firms choose very different allocations of growth and efficiency. Consistent with the idea that firms should pivot from growth to efficiency as they mature, we show that a significant part of this heterogeneity relates to firms' age. In particular, the ratio of short-term effort to investment increases significantly from firms' IPO decade to the next. This increased focus on efficiency is present across industries and firms' cohorts, i.e., when they went public. The average increase in the ratio of short-term effort to investment ranges between 15% in the Manufacturing industry to 36% for Consumer Goods. For the Technology and Healthcare sectors, this ratio increases on average by 27% and 24%.

We find that these results cannot be fully explained by changes in fundamentals, such as the elasticity of earnings to capital or the volatility of shocks to firms' capital stock. For example, firms that went public in the 70s, 80s or 90s increased significantly their focus on efficiency relative to growth from the first decade as public firms to the next even if the earnings elasticity of capital increased. Yet, cross-sectional variation in fundamentals matters. For example, the volatility of shocks to the capital stock is negatively and significantly correlated with investment during firms' IPO decade but not later. And a higher earnings elasticity of capital is associated, on average, with lower short-term effort and lower ratios of short-term effort to investment. To some extent, amongst firms of the same age and in the same industry those with riskier and less productive capital focus more on efficiency and less on growth, if not systematically at all stages in their life.

Cross-sectionally, short-term effort and investment policies are strongly related to product market outcomes. For every additional one standard deviation difference in the level of short-term effort, the firm's marginal cost markup is higher by 10 to 14 percentage points and its annual sales are higher by 30% to 33% on average during the same decade. The investment rate is not correlated with the markup in the same decade. It is though, significantly negatively correlated with annual sales: a one standard deviation difference in the investment rate is associated with annual sales that are lower by 50% on average. In short, efficient firms are large and charge high markups while growth firms tend to be smaller and have less market power.

Furthermore, we show that different short-term effort and investment policies when firms are young have long-term consequences. In a nutshell, firms focused on growth when young achieve the highest markups in the long-term, whereas firms focused on efficiency have higher chances of surviving in the long-term. For example, a one standard deviation increase in the investment rate within the IPO decade predicts a price-cost markup that is higher by 8, 9 and 13 percentage points in the three following quinquenia. But such an increase in investment is also associated with a decrease of 0.24 in the probability of surviving the IPO decade.

We complete the analysis with two exercises to check the external validity of our estimates. First, we show that a sorting of firms based on the ratio of short-term effort to investment, calculated between and 1997 and 2006, predicts well which firms survived or failed during the Great Financial Crisis of 2008 to 2009. Indeed, the short-term effort-to-investment ratio is higher by 16.5% for the average survivor relative to the average firm that failed. Second, we show that our estimates of investment, short-term effort and the earnings elasticity of capital, help explain the cross-section of returns via the supply channel of the investment CAPM (Hou, Xue, and Zhang, 2015). In particular, we find that firms with higher short-term effort or higher earnings elasticity of capital, which, being more profitable should have a higher excess returns, have indeed higher profitability factor betas. Moreover, firms with higher estimated investment rates, which should have lower excess returns, have indeed lower investment factor betas. That is, our estimates of firms' policies and deep parameters can explain firms' different exposures to the investment and profitability factors as theory would predict.

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, Stulz, and Waelchli (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)).[2] 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

[2] 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.

firms invest in intangible and tangible capital early in their cycle, acquire assets as they mature, and divest as they decline. Bustamante, Cujean, and Frésard (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, Rivera, and Wong (2021) and Gryglewicz, Mayer, and Morellec (2020) also consider that firms can exert short-term 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' short-term effort, and analyse empirically its determinants. Methodologically, our model's estimation resembles that used by Gryglewicz, Mancini, Morellec, Schroth, and Valta (2022) to disentangle empirically the permanent and transitory shock of firms' cash flows.

The structure of the paper proceeds as follows. Section 2 presents the firm model and derives the optimal policies. Section 3 discusses the estimation method and data. In Section 4 we describe our estimation results. Section 5 focuses on growth versus efficiency choices. Section 6 presents an empirical asset pricing application as a validation of our estimates. Section 7 concludes. The appendix collects technical derivations.

2 A model of optimal short-term efficiency effort

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 $(\Omega, \mathcal{F}, \mathbb{F}, Q)$ satisfying the usual conditions.

2.1 Earnings

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

$$dK_t = (I_t - \delta_K K_t)\, dt + \sigma_K K_t\, dW_{K,t} \tag{1}$$

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

$$dL_t = (H_t - \delta_L L_t)\, dt + \sigma_L L_t\, dW_{L,t} \tag{2}$$

where $H_t > 0$ 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. 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 $\sigma_L > 0$. These dynamics imply that shocks to capital or labor stocks have permanent effects. We interpret them as embodied technological progress or training of the work force.

Operating earnings at any time $t \geq 0$ are proportional to a Cobb–Douglas function $K_t^{\gamma} L_t^{\beta}$ with decreasing returns to scale, in which $0 < \gamma < 1$ and $0 < \beta < 1$ are the elasticity of earnings to capital and labor, and $\gamma + \beta \leq 1$. In addition to permanent shocks to capital and labor growth, earnings are subject to short-lived shocks, dA_t. The A_t process is the firm's efficiency level, which is *controlled* by the choice of short-term effort, s_t, and evolves as

$$dA_t = s_t\, dt + \sigma_A\, dW_{A,t} \tag{3}$$

where the standard Brownian motion $W_{A,t}$ is a source of exogenous shocks with 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. For simplicity, all Brownian motions are assumed to be uncorrelated. In the appendix we show that this assumption is not essential for estimation, which can be adapted to any arbitrary correlation structure between the three shocks.

Operating earnings over the time increment dt are given by $K_t^{\gamma} L_t^{\beta} dA_t$. All other things constant, higher levels of s_t imply higher earnings. Note too that earnings can be negative if and only if dA_t is negative. The earnings model in (1)–(3) nests popular models in the literature. If $I_t - \delta_K K_t = \sigma_K = 0$ (constant capital stock), $\gamma = 1$ (constant return to scale of capital), and $\beta = 0$ (no labor factor), we obtain the stationary cash flow process of dynamic agency models (see DeMarzo and Sannikov (2006) or DeMarzo, Fishman, He, and Wang (2012)) and liquidity management models (see Décamps, Mariotti, Rochet, and Villeneuve (2011) or Bolton, Chen, and Wang (2011)). Our earnings model also includes shocks with permanent effects, which must be empirically identified. If $\sigma_A = 0$ (no short-term shocks), $I_t - \delta_K K_t$ is proportional to K_t, $\beta = 0$, and $\gamma = 1$, we obtain the model with time-varying profitability that is commonly used in dynamic capital structure (see Leland and Toft (1996), Leland (1998), Goldstein, Ju, and Leland (2001), Hackbarth, Miao, and Morellec (2006), or Strebulaev (2007)) and real-options models (see Abel and Eberly (1994) or Carlson, Fisher, and Giammarino (2004)). Unlike such models with permanent shocks only, combining short-term and permanent shocks allows the model to better match the earnings and assets volatilities in the data (see Gorbenko and Strebulaev (2010) and Gryglewicz et al. (2022)). Finally, if $\beta = 0$ and $\gamma = 1$, we obtain the dynamic agency model recently used by Gryglewicz et al. (2020) and Hackbarth et al. (2021).

2.2 Input adjustment costs

Adjusting short-term effort, investment or hiring is increasingly costly. We consider the following quadratic adjustment cost function

$$C(s_t, I_t, H_t, K_t, L_t) = \frac{\lambda_s}{2} s_t^2 K_t^{\gamma} L_t^{\beta} + \frac{\lambda_K}{2} \left(\frac{I_t}{K_t} \right)^2 K_t^{\gamma} L_t^{\beta} + \frac{\lambda_L}{2} \left(\frac{H_t}{L_t} \right)^2 K_t^{\gamma} L_t^{\beta} \tag{4}$$

where the parameters $\lambda_s, \lambda_K, \lambda_L$ are strictly positive. As in Hayashi (1982), 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.

2.3 Firm policies

Management chooses short-term effort, 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

$$V(K_0, L_0) = \sup_{s,I,H} \mathbb{E} \int_0^\infty e^{-rt}(K_t^\gamma L_t^\beta dA_t - C(s_t, I_t, H_t, K_t, L_t)\, dt) \tag{5}$$

where the expectation $\mathbb{E}$ is conditional on the starting values of capital and labor, K_0 and L_0. Standard arguments yield that the firm value V satisfies the following Hamilton–Jacobi–Bellman (HJB) equation

$$\begin{aligned} rV(K, L) = \sup_{s,I,H} \{ & K^\gamma L^\beta s - C(s, I, H, K, L) + V_K(I - \delta_K K) + V_L(H - \delta_L L) \\ & + \frac{1}{2} V_{KK}\sigma_K^2 K^2 + \frac{1}{2} V_{LL}\sigma_L^2 L^2 \} \end{aligned} \tag{6}$$

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, which is maximized by choosing short-term effort, investment and hiring. 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 equity value. The last two terms are the effects of volatility of capital and labor.

Firm's policies are obtained by solving the system of first-order conditions to (6), which are

$$K^\gamma L^\beta = C_s, \quad V_K = C_I, \quad V_L = C_H \tag{7}$$

where C_x is the derivative of $C(s, I, H, K, L)$ with respect to x. Each condition equates the marginal value of each input to its marginal cost. We guess, and verify in the appendix, 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 $\gamma, \beta, \lambda_s, \lambda_K, \lambda_L, \delta_K, \delta_L, \sigma_K, \sigma_L$ and σ_A.

Solving, we obtain the optimal policies

$$s^* = \frac{1}{\lambda_s}, \qquad I_t^* = \frac{c\gamma}{\lambda_K} K_t \equiv i^* K_t, \qquad H_t^* = \frac{c\beta}{\lambda_L} L_t \equiv h^* L_t. \tag{8}$$

The optimal level of short-term effort, s^*, is constant along the steady-state growth path and inversely related to its marginal adjustment cost, λ_s. The steady-state 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.

In this model, higher levels of short-term effort make the firm more valuable, which in turn increases the marginal benefit of investment. Hence, lower short-term effort costs λ_s imply higher optimal short-term effort and, therefore, a higher optimal investment rate. The left panel of Figure 1 plots the different combinations of optimal i^* and s^* as λ_s varies. For the blue or black lines, along which all other parameters are kept constant, i^* and s^* are positively correlated. However, keeping λ_s constant, an increase in the capital adjustment costs (from $\lambda_K = 2.5$ black line, to $\lambda_K = 3.2$ blue line) reduces optimal investment. Therefore, even if short-term effort 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, short-term and capital adjustment costs were inversely related across firms.

Insert Figure 1 here

The right panel of Figure 1 shows the optimal combinations of efficiency and investment for different short-term effort 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 short-term adjustment costs and capital shocks volatility were negatively correlated across firms, then so would be short-term effort and investment, despite being earnings complements.

2.4 Robustness

The Cobb–Douglas specification implies that short-term effort is complementary to either investment or hiring in the earnings function. However, the interaction between short-term effort and investment or hiring policies predicted by the model across firms depends on how the adjustment costs function parameters and the capital and labor stocks volatilities are jointly distributed in the cross-section. As we show below, we can estimate the model using the time series of earnings, investment, hiring, and capital and labor stocks identifying the short-term effort policy at a very granular level. We can therefore characterize the joint distribution of the three policies and of most model parameters across all public firms.

Specifically, all policies and all parameters but λ_K and λ_L are identified. As we show in the appendix, this result is robust to other more general specifications of the model. For example, we can identify the same parameters as in the benchmark model if we allowed the shocks to the capital and labor stocks to be correlated, or if we included also linear adjustment costs on each policy, or if we included adjustment costs interactions, e.g., substitutes or complements, between investment and hiring. Allowing for cost adjustment interactions between short-term effort and any other policy compromises only the identification of λ_s, but not the identification of s^*.

3 Estimation and Data

We describe in this section our method to estimate the model's policies and parameters with the maximum possible level of granularity. 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.

3.1 Steady-state dynamics

Plugging the optimal firm's policies in the dynamics of capital, labor and short-term shocks, i.e., substituting (8) into (1)–(3), gives the controlled dynamics of these processes. The result is the optimal time series trajectory of each controlled variable, which is therefore free of any endogeneity bias. In fact, the model describes how each endogenous variable (short-term effort, investment and hiring) determines observable (possibly noisy) quantities like capital and labor stocks through exogenous model parameters which are the objective of the inference procedure. Along the steady-state path, capital and labor stocks follow geometric Brownian motions

$$dK_t = (i^* - \delta_K)K_t\, dt + \sigma_K K_t\, dW_{K,t} \tag{9}$$

$$dL_t = (h^* - \delta_L)L_t\, dt + \sigma_L L_t\, dW_{L,t} \tag{10}$$

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

$$dA_t = s^*\, dt + \sigma_A dW_{A,t}. \tag{11}$$

These dynamics form the basis to estimate model parameters.

3.2 Estimation

Estimation of equations (9) to (11) 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 error-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. This issue cannot be fixed by taking logarithms because operating earnings are often negative at the firm level. Given equations (9) to (11), the most efficient estimation procedure while addressing these problems is by 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 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

$$\log(K_{t+1}) = \log(K_t) + \mu_K + w_{1,t}, \tag{12}$$

$$\log(L_{t+1}) = \log(L_t) + \mu_L + w_{2,t}, \tag{13}$$

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 $\mathbf{w}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{Q})$ 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

$$z_{1,j,t} = s^* K_t^{\gamma} L_t^{\beta} + v_{1,j,t} \tag{14}$$

$$z_{2,j,t} = K_t + v_{2,j,t} \tag{15}$$

$$z_{3,j,t} = L_t + v_{3,j,t} \tag{16}$$

$$z_{4,j,t} = i^* K_t + v_{4,j,t} \tag{17}$$

$$z_{5,j,t} = h^* L_t + v_{5,j,t} \tag{18}$$

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 $\sigma_{v,1}^2, \ldots, \sigma_{v,5}^2$. 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 $\mathbf{v}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{R})$ and $\mathbf{R}$ a diagonal covariance matrix. Altogether, this state space model has 14 parameters: three related to firm policies, s^*, 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, $\sigma_{v,1}^2, \ldots, \sigma_{v,5}^2$.

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 $z_t \equiv [z_{1,1,t}, \dots, z_{5,1,t}, \dots, z_{1,40,t}, \dots, z_{5,40,t},]$, i.e., earnings, capital, labor, investment and hiring of the N firms in each group and for $t = 1, \dots, T$:

$$\sum_{t=1}^{T} -\frac{1}{2}\left[5N\log(2\pi) + \log|F_{t|t-1}| + (z_t - \hat{z}_{t|t-1})' F_{t|t-1}^{-1}(z_t - \hat{z}_{t|t-1})\right] \tag{19}$$

where $z_{t|t-1}$ 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.

3.3 Identification and inference

Estimation of the state space model in equations (12) to (18) allows for identification of all three policies: Because the steady-state rates of investment, i^*, hiring, h^* and short-term effort, s^* are constant, they are recovered as the slope parameters of the earnings (equation 14), investment (equation 17) and hiring (equation 18) measurement equations, respectively. Amongst the model's deep parameters, the earnings' elasticities to capital and labor, γ and β, are identified directly off equation (14) 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 errors in the transition equations (12) and (13). 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.

Adjustment costs parameters are generally not identified by this estimation method. The marginal costs of investment and hiring (λ_K and λ_L) are absorbed in the investment and hiring rates, $i^* = (c\gamma/\lambda_K)$ and $h^* = (c\beta/\lambda_L)$, where c is a constant that is a function of all the model's parameters. And while we can recover the marginal costs of effort λ_s from $1/s^*$ in this version of the model, this parameter would not be identified for more general specifications of the investment adjustment costs function.

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 2, which shows the sensitivity of two model-implied moments to s^* and σ_K. Both curves in blue represent all the combinations of values for the short-term effort policy, s^*, 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 short-term effort if shocks to the capital stock were more volatile. And for a given level of volatility, less short-term effort would imply a lower earnings growth rate, e.g., from 2% to 1.9% (dash-dotted blue line).

Insert Figure 2 here

The black isocurves plot the combinations of s^* and σ_K that imply the same earnings growth variance, $V[CF_{t+1}/CF_t]$, *ceteris paribus.* Keeping s^* 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 0.3% (dash-dotted black line) to 0.36% (solid line). Moreover, the black isocurves have a negative slope, meaning that with higher s^*, the same earnings growth volatility is obtained with lower σ_K. Further, Figure 2 shows that there is a unique combination of s^* and σ_K that produce any given combination of earnings growth rates and volatility. Thus, the model will infer high level of both short-term effort 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.

3.4 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 2017 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, 2017), 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 1 defines each variables and presents its summary statistics.

Insert Table 1 here

3.5 Firm grouping

We estimate the earnings model in (12)–(18) 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.[3] For $N = 10$, the permanent shock commonality assumption is almost innocuous, and significantly weaker than grouping firms even at the four-digit SIC code level.[4,5] Applying the criteria above, our sample of 18,026 firms is split

[3] 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 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.

[4] For example, Bates, Kahle, and Stulz (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.

[5] 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.

into 1,801 cohort-5 Fama and French (1997) industry -earnings growth groups.

Table 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 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, Eeckhout, and Unger (2020). In a nutshell, our grouping approach produces many small and heterogeneous groups of alike firms.

Insert Table 2 here

4 Estimation results

Table 3 presents estimates of the policies i^*, h^*, and s^*, 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 (2017) 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%, with 95% of the group estimates between 6% and 32%. The average of the short-term effort 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, s^* also varies significantly across firm groups: 95% of the estimates range between 0 and 0.64.

Insert Table 3 here

Table 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 2, correct inference about s^* and i^* depends crucially on controlling for variation in σ_K.[6] 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.

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.[7]

Figure 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

[6]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).

[7]Figures IA.1 and IA.2 in the Internet Appendix show the distributions of s^*, h^*, and i^* by cohort. The absolute average estimated short-term effort intensity decreases monotonically with the decade in which the IPO occurred. In contrast, the average hiring rate increases as the investment rate has a U shape and is highest for firms going public between 2010 and 2019. In these plots, cross-cohort differences may be due to age differences between the earliest and most recent cohorts.

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.

Insert Figure 3 here

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 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 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.

Insert Figure 4 here

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.[8] 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 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.

Insert Figure 5 here

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 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 short-term effort during the same transition.

Insert Figure 6 here

4.2 Investment and short-term effort over time

We compare short-term effort and investment policies in Figure 7, which plots the time series of the average of the ratio of optimal short-term effort to optimal investment, s^*/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).

Insert Figure 7 here

Figure 7 shows that, amongst survivors, the average s^*/i^* ratio increased significantly from the IPO decade to the next regardless of the cohort. The later the cohort, the larger the increase: For

[8] We show in Appendix A.1 that $\partial i^*/\partial\sigma_K^2 < 0$.

firms that went public in the 2000s, the average ratio almost doubles, from 1.5 to 2.75. Except for the 70s cohort, the s^*/i^* ratio is also significantly higher for firms that survived rather than failed during the decade of the IPO. Figure 8 explores whether the difference between the average s^*/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 s^*/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 8 shows that, conditional on a firm's fate after the IPO decade, the average s^*/i^* ratio increases with the firm's age at the time of IPO. However, these differences are relatively small compared to the differences in s^*/i^* between failed and surviving firms within each age group.

Insert Figure 8 here

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 short-term effort relative to capital investment over time. Second, that controlling for age, firms going public with higher short-term effort to investment ratios are more likely to survive and mature. In short, a firm's prevalence is related to its s^* and i^* policies early on.

4.3 Investment and short-term effort across industries

Figure 9 displays the distributions of the s^*/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 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 $\hat{s}^*/\hat{i}^*$. 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 9 shows that the $\hat{s}^*/\hat{i}^*$ 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 0.12) in the Healthcare industry, where the change is most pronounced (Panel B of Table 4), but it is also economically and statistically significant for the Consumer Goods industry, 0.41 (0.10), Manufacturing, 0.29 (0.11), and the Technology sector, 0.37 (0.09). For all industries, the $\hat{s}^*/\hat{i}^*$ ratios are more dispersed in the second decade, as the distribution skews more to the right.

Insert Figure 9 here

Insert Table 4 here

Table 5 describes in detail the changes in the $\hat{s}^*/\hat{i}^*$ 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 $\hat{s}^*/\hat{i}^*$ 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{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 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 $\hat{s}^*/\hat{i}^*$ 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 short-term effort 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 1980s or Technology since 2000, occurs despite a decrease in $\hat{\sigma}_K$.

Insert Table 5 here

If not the case on average, the coefficients in Table 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 00s entrants not in Consumer Goods, 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 short-term effort 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.

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.

5.1 Determinants of short-term effort and investment policies

Table 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 $\hat{s}^*$, $\hat{i}^*$, or the ratio $\hat{s}^*/\hat{i}^*$ 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 short-term effort. 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 s nor i in the next decade. Instead, and similar to the time series analysis, differences in s^*, i^* or their ratio are better explained by heterogeneity in the estimated capital elasticity of earnings, $\hat{\gamma}$: the third row of Table 6 shows negative and statistically significant coefficients of s^* or s^*/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.

Insert Table 6 here

The coefficients on the cohort fixed effects reveal that the largest s^*/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 90s or 2000s. 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 short-term effort, for any firm but only in the decade of IPO and not afterwards. To summarize, the cross-sectional heterogeneity in s^* 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 s^*/i^* ratios.

5.2 Policies and outcomes for young firms

Table 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. (2020) (Panel A) or of the logarithm of annual sales (Panel B) on the short-term effort 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.

Insert Table 7 here

The coefficient estimates in the first column of Table 7 show that the surviving firms with the highest short-term effort 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 short-term effort provision are positively correlated with differences in the markup, and the relation is statistically and economically significant: one standard deviation differences in s^* 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 short-term effort, they are already more focused on efficiency as opposed to growth and can charge higher markups.

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 8. Qualitatively, the results are very similar for this decade than the previous. Namely, that firms that went public older, which exhibit higher short-term effort but lower investment, are larger and have higher markups on average.

Insert Table 8 here

Quantitatively, the relation between short-term effort policy and the markup or sales is bigger: a one standard deviation increase in s^* is associated with a 14.2% increase in the average markup and 33.1% more sales. In addition, firms with the highest short-term effort 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 s^* 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.

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 9 reports the coefficient estimates from these predictive regressions. The first column shows that higher short-term effort predicts higher markups, higher sales and higher sales growth in the five-year period following the IPO decade: For each outcome, the coefficients of s^* 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 short-term effort. 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 7 already shows that the firms least likely to survive past the IPO decade are those with the lowest s^*/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.

Insert Table 9 here

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:

$$\text{Prob[Firm } f \text{ survives IPO decade]} = \underset{(0.09)}{1.06} + \underset{(0.10)}{1.08}\, s_f^* - \underset{(0.27)}{3.05}\, i_f^* - \underset{(0.25)}{1.95}\, \sigma_{K,f} - \underset{(0.27)}{0.37}\, \mu_{K,f} + \underset{(0.01)}{0.02}\, \text{Prob[U.S. goes into Recession]} \quad (20)$$

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 short-term effort 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 (20) are as expected and are consistent with our time series analysis: Firms with higher short-term effort 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 short-term effort 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 short-term effort 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.

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 s^* 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 s^*/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 10 shows the average s^*/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 short-term effort relative to the investment rate than the average failed firm.

Insert Figure 10 here

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 short-term effort, 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, Whited, and Zhang, 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 s^* and γ, given that profitability equals $c\gamma K^{\gamma-1}L^{\beta}$ and that $\partial c/\partial s^* > 0$ (see Appendix 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 short-term effort 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 3.5) 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.[9] Then, we regress the cross section of each estimated beta on the cross-sectional estimates of s^*, i^* and γ, controlling for cohort and industry fixed effects.

Table 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 short-term effort. 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

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

theory.

As discussed above, our estimates of short-term effort 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 short-term effort 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 s^* and γ, and therefore have a higher exposure to the profitability factor. Table 10 also analyzes the exposure to the size factor. The third column shows that the size beta, β_{ME}, loads negatively on short-term effort 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 s^* but low i^*.

Insert Table 10 here

In sum, our estimates of short-term effort and investment, which appear to capture the stage in the 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.

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 short-term effort. 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 short-term effort 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.

References

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Hoberg, G., and V. Maksimovic. 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.

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

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

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

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

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

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

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

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

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

Shumway, R., and D. Stoffer. 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.

Zhang, L. 2017. The investment CAPM. *European Financial Management* 23:545–603.

Appendix

A Model Solution and Robustness of Policies

This section discusses the solution of the HJB equation (6) and the robustness of the optimal policies to various specifications of the cost function and shock correlations.

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 (8) in the HJB equation (6) gives the following equation in c

$$rc = \frac{1}{\lambda_s} - \left(\frac{1}{2\lambda_s} + \frac{c^2\gamma^2}{2\lambda_K} + \frac{c^2\beta^2}{2\lambda_L}\right) + c\gamma\left(\frac{c\gamma}{\lambda_K} - \delta_K\right) + c\beta\left(\frac{c\beta}{\lambda_L} - \delta_L\right) + \frac{1}{2}c\gamma(\gamma-1)\sigma_K^2 + \frac{1}{2}c\beta(\beta-1)\sigma_L^2 \tag{21}$$

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

$$a = \frac{\gamma^2}{2\lambda_K} + \frac{\beta^2}{2\lambda_L} \tag{22}$$

$$b = -\gamma\delta_K - \frac{1}{2}\gamma(1-\gamma)\sigma_K^2 - \beta\delta_L - \frac{1}{2}\beta(1-\beta)\sigma_L^2 - r \tag{23}$$

$$d = \frac{1}{2\lambda_s} \tag{24}$$

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 Gryglewicz et al. (2020), which is attained when agency conflicts are absent in their setting. Second order conditions of the optimal policies s^*, i^*, and h^*, are, respectively,

$$-C_{ss} = -\lambda_s K^{\gamma}L^{\beta}, \quad -C_{II} = -\lambda_K K^{\gamma-2}L^{\beta}, \quad -C_{HH} = -\lambda_L K^{\gamma}L^{\beta-2} \tag{25}$$

which are all negative, because $K > 0$ and $L > 0$ follow geometric Brownian motions in equilibrium, ensuring that the objective function (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. For example, firm value is increasing in the short-term effort $s^* = 1/\lambda_s$

$$\frac{\partial c}{\partial s^*} = \frac{1}{2\sqrt{\Delta}} > 0. \tag{26}$$

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

$$\frac{\partial c}{\partial \sigma_K^2} = \frac{\gamma(1-\gamma)}{4a}\left(1 + \frac{b}{\sqrt{\Delta}}\right) < 0 \tag{27}$$

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

$$\frac{\partial i^*}{\partial \sigma_K^2} = \frac{\gamma}{\lambda_K}\frac{\partial c}{\partial \sigma_K^2} < 0. \tag{28}$$

A.2 Alternative Model Specifications

The optimal policies in the baseline model are such that the short-term effort s^* is constant, the investment I^* is linear in the capital stock K, and the hiring of new labor force H^* is linear in the total work force L. This section shows that the functional forms of these policies are robust to a number of more general cost function and model specifications. Although these extended specifications capture relevant economic aspects, 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.

A.2.i Complementarity or substitution of inputs

Complementarity or substitution of inputs can be accommodated in the firm model by extending the cost function (4). As inputs we first consider short-term effort and investment. Then, the cost function takes the form

$$C(s, I, H, K, L) = \frac{\lambda_s}{2}s^2K^\gamma L^\beta + \frac{\lambda_K}{2}\left(\frac{I}{K}\right)^2 K^\gamma L^\beta + \frac{\lambda_L}{2}\left(\frac{H}{L}\right)^2 K^\gamma L^\beta + \lambda_{sK}s\frac{I}{K}K^\gamma L^\beta \tag{29}$$

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

$$\frac{\partial C(s, I, H, K, L)}{\partial s} = \lambda_s\, sK^\gamma L^\beta + \lambda_{sK}\frac{I}{K}K^\gamma L^\beta$$

which is increasing in I when $\lambda_{sK} > 0$. Similarly, an increase in short-term effort makes investment more expensive when $\lambda_{sK} > 0$.

Even if the cost function (29) features an additional term, the functional form of the optimal polices are unchanged. The first order condition (FOC) for s is

$$K^\gamma L^\beta = C_s$$
$$K^\gamma L^\beta = \lambda_s\, sK^\gamma L^\beta + \lambda_{sK}I\,K^{\gamma-1}L^\beta$$

which implies that the optimal short-term effort s^* is

$$s^* = \frac{K^\gamma L^\beta}{\lambda_s K^\gamma L^\beta} - \frac{\lambda_{sK} I^* K^{\gamma-1} L^\beta}{\lambda_s K^\gamma L^\beta} = \frac{1}{\lambda_s} - \frac{\lambda_{sK}}{\lambda_s}\frac{I^*}{K}.$$

The second order condition for s^* is always negative, $-\lambda_s K^\gamma L^\beta < 0$. Similarly, the FOC for I^* is

$$\begin{aligned} V_K &= C_I \\ V_K &= \lambda_K I K^{\gamma-2} L^\beta + \lambda_{sK} s\, K^{\gamma-1} L^\beta \end{aligned}$$

which implies that the optimal investment I^* is

$$I^* = \frac{V_K}{\lambda_K K^{\gamma-2} L^\beta} - \frac{\lambda_{sK} s^* K^{\gamma-1} L^\beta}{\lambda_K K^{\gamma-2} L^\beta} = \frac{c\gamma}{\lambda_K} K - \frac{\lambda_{sK}}{\lambda_K} s^* K$$

where in the second equality we used $V(K, L) = cK^\gamma L^\beta$. The second order condition for I^* is always negative, $-\lambda_K K^{\gamma-2} L^\beta < 0$.

To jointly determine I^* and s^*, the system to be solved is given by

$$\begin{aligned} I^* &= \frac{c\gamma}{\lambda_K} K - \frac{\lambda_{sK}}{\lambda_K} s^* K \\ s^* &= \frac{1}{\lambda_s} - \frac{\lambda_{sK}}{\lambda_s}\frac{I^*}{K}. \end{aligned}$$

Solving for I^* gives

$$\begin{aligned} I^* &= \frac{c\gamma}{\lambda_K} K - \frac{\lambda_{sK}}{\lambda_K} s^* K \\ &= \frac{c\gamma}{\lambda_K} K - \frac{\lambda_{sK}}{\lambda_K}\left(\frac{1}{\lambda_s} - \frac{\lambda_{sK}}{\lambda_s}\frac{I^*}{K}\right) K \\ \left(1 - \frac{\lambda_{sK}^2}{\lambda_K \lambda_s}\right) I^* &= \left(\frac{c\gamma}{\lambda_K} - \frac{\lambda_{sK}}{\lambda_K}\frac{1}{\lambda_s}\right) K \end{aligned}$$

which yields that I^* is linear in K and consequently s^* is constant like in the baseline model.

In the cost function (29), replacing the last term by $\lambda_{sL} sHK^\gamma L^{\beta-1}$ captures complementarity or substitution between short-term effort and hiring, depending on the sign of λ_{sL}. Moreover, adding the term $\lambda_{sL} sHK^\gamma L^{\beta-1}$ to the cost function (29) yields interactions among the three inputs, while preserving the functional form of the optimal policies.

Complementarity or substitution between capital and labor can be modelled by extending the cost function (4) to

$$C(s, I, H, K, L) = \frac{\lambda_s}{2} s^2 K^\gamma L^\beta + \frac{\lambda_K}{2}\left(\frac{I}{K}\right)^2 K^\gamma L^\beta + \frac{\lambda_L}{2}\left(\frac{H}{L}\right)^2 K^\gamma L^\beta + \lambda_{KL}\frac{I}{K}\frac{H}{L} K^\gamma L^\beta$$

where the last term yields that $\partial^2 C/(\partial I\, \partial H) \neq 0$. Similar calculations as above show that the optimal policies retain their functional form. The first order condition (FOC) for I is

$$\begin{aligned} V_K &= C_I \\ V_K &= \lambda_K I K^{\gamma-2} L^\beta + \lambda_{KL} H K^{\gamma-1} L^{\beta-1} \end{aligned}$$

which implies that the optimal investment I^* is given by

$$I^* = \frac{V_K}{\lambda_K K^{\gamma-2} L^\beta} - \frac{\lambda_{KL} H^* K^{\gamma-1} L^{\beta-1}}{\lambda_K K^{\gamma-2} L^\beta} = \frac{c\gamma}{\lambda_K} K - \frac{\lambda_{KL}}{\lambda_K} \frac{H^*}{L} K \tag{30}$$

where in the second equality we used $V(K, L) = cK^\gamma L^\beta$. Similarly, the FOC for H is

$$V_L = C_H$$
$$V_L = \lambda_L H K^\gamma L^{\beta-2} + \lambda_{KL} I K^{\gamma-1} L^{\beta-1}$$

which implies that the optimal hiring of new work force H^* is given by

$$H^* = \frac{V_L}{\lambda_L K^\gamma L^{\beta-2}} - \frac{\lambda_{KL} I^* K^{\gamma-1} L^{\beta-1}}{\lambda_L K^\gamma L^{\beta-2}} = \frac{c\beta}{\lambda_L} L - \frac{\lambda_{KL}}{\lambda_L} \frac{I^*}{K} L. \tag{31}$$

Solving (30) and (31) for I^* and H^* gives

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

Thus, I^* is again linear in K, which in turn gives that H^* is linear in L. The FOC for s^*, and its solution, is the same as in the baseline model.

A.2.ii Correlated shocks

In the baseline model the Brownian shocks to capital and labor in (1) and (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 in $K^\gamma L^\beta$ cancel out, and the constant c solves a similar equation to (21). Specifically, the new HJB equation with the additional term $V_{KL}\rho\sigma_K\sigma_L KL$ is

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

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

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

A.2.iii Linear-quadratic adjustment cost function

The quadratic adjustment cost (4) implies that disinvesting, i.e., selling capital stock, generates no revenue. This assumption can be relaxed by considering a linear-quadratic cost function

$$C(s, I, H, K, L) = \frac{\lambda_s}{2} s^2 K^\gamma L^\beta + \frac{\lambda_K}{2} \left(\frac{I}{K}\right)^2 K^\gamma L^\beta + \frac{\lambda_L}{2} \left(\frac{H}{L}\right)^2 K^\gamma L^\beta + \alpha_K \left(\frac{I}{K}\right) K^\gamma L^\beta$$

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

$$V_K = \lambda_K I K^{\gamma-2} L^\beta + \alpha_K K^{\gamma-1} L^\beta$$

and the optimal investment is

$$I^* = \frac{V_K - \alpha_K K^{\gamma-1} L^\beta}{\lambda_K K^{\gamma-2} L^\beta} = \left(\frac{c\gamma - \alpha_K}{\lambda_K}\right) K$$

where in the second equality we use $V(K, L) = cK^\gamma L^\beta$. The investment ratio I^*/K is still constant like in the baseline model. FOCs and policies of the other inputs are unchanged.

B Model Estimation with Unscented Kalman Filter

This section provides a detailed exposition of the estimation method used in Section 3.2. We describe the state space model, the unscented Kalman filter to compute the likelihood function, and how we handle missing observations.

B.1 The state space model

The state space model in (12)–(18) 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 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,

$$x_{t+1} = \phi_0 + \phi_1 x_t + w_t \tag{32}$$

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

$$z_t = h(x_t) + v_t \tag{33}$$

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, $\sigma^2_{v,1}, \ldots, \sigma^2_{v,5}$, 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

$$h(x_t) = [s^* e^{\gamma x_{1,t}} e^{\beta x_{2,t}} \mathbf{1}',\ e^{x_{1,t}} \mathbf{1}',\ e^{x_{2,t}} \mathbf{1}',\ i^* e^{x_{1,t}} \mathbf{1}',\ h^* e^{x_{2,t}} \mathbf{1}']' \tag{34}$$

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.

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 $\hat{x}_{t|t-1} = \mathbb{E}_{t-1}[x_t]$ and $\hat{z}_{t|t-1} = \mathbb{E}_{t-1}[z_t]$ 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 $\hat{x}_t = \mathbb{E}_t[x_t]$ 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

$$\hat{x}_{t|t-1} = \phi_0 + \phi_1 \hat{x}_{t-1} \tag{35}$$

$$P_{t|t-1} = \phi_1 P_{t-1} \phi_1' + Q_t \tag{36}$$

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

$$\hat{z}_{t|t-1} = h_0 + h_1 \hat{x}_{t|t-1} \tag{37}$$

$$F_{t|t-1} = h_1 P_{t|t-1} h_1' + R. \tag{38}$$

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

$$\hat{x}_t = \hat{x}_{t|t-1} + K_t(z_t - \hat{z}_{t|t-1}) \tag{39}$$

$$P_t = P_{t|t-1} - K_t\, F_{t|t-1}\, K_t' \tag{40}$$

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 $K_t = P_{t|t-1} h_1' F^{-1}_{t|t-1}$.

In our setting, the function $h(x_t)$ is nonlinear, and the Kalman filter has to be modified. Nonlinear 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

$$
\begin{array}{rclrcll}
\hat{\chi}^0_{t|t-1} & = & \hat{x}_{t|t-1}, & \omega^0 & = & \frac{\kappa}{L+\kappa} & \\
\hat{\chi}^i_{t|t-1} & = & \hat{x}_{t|t-1} + \left(\sqrt{(L+\kappa)P_{t|t-1}}\right)_i, & \omega^i & = & \frac{1}{2(L+\kappa)}, & i = 1, \ldots, L \\
\hat{\chi}^i_{t|t-1} & = & \hat{x}_{t|t-1} - \left(\sqrt{(L+\kappa)P_{t|t-1}}\right)_i, & \omega^i & = & \frac{1}{2(L+\kappa)}, & i = L+1, \ldots, 2L
\end{array}
\tag{41}
$$

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, (37) and (38) are replaced by

$$
\hat{z}_{t|t-1} = \sum_{i=0}^{2L} \omega^i \, h(\hat{\chi}^i_{t|t-1}) \tag{42}
$$

$$
F_{t|t-1} = \sum_{i=0}^{2L} \omega^i (h(\hat{\chi}^i_{t|t-1}) - \hat{z}_{t|t-1})(h(\hat{\chi}^i_{t|t-1}) - \hat{z}_{t|t-1})' + R. \tag{43}
$$

The update step is still given by (39) and (40), but with K_t computed as

$$
K_t = \sum_{i=0}^{2L} \omega^i (\hat{\chi}^i_{t|t-1} - \hat{x}_{t|t-1})(h(\hat{\chi}^i_{t|t-1}) - \hat{z}_{t|t-1})' F^{-1}_{t|t-1}. \tag{44}
$$

Finally, the log-likelihood function is given by

$$
\sum_{t=1}^{T} -\frac{1}{2} \left[5N \log(2\pi) + \log |F_{t|t-1}| + (z_t - \hat{z}_{t|t-1})' F^{-1}_{t|t-1} (z_t - \hat{z}_{t|t-1}) \right] \tag{45}
$$

where T is the time series length of the sample. Model estimates are obtained by maximizing the log-likelihood (45) with respect to the model parameters: s^*, (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 $\hat{x}_t$.

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 (33) 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 (33) by S_t and use this measurement equation to run the UKF. Finally, compute the log-likelihood in (45) 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.

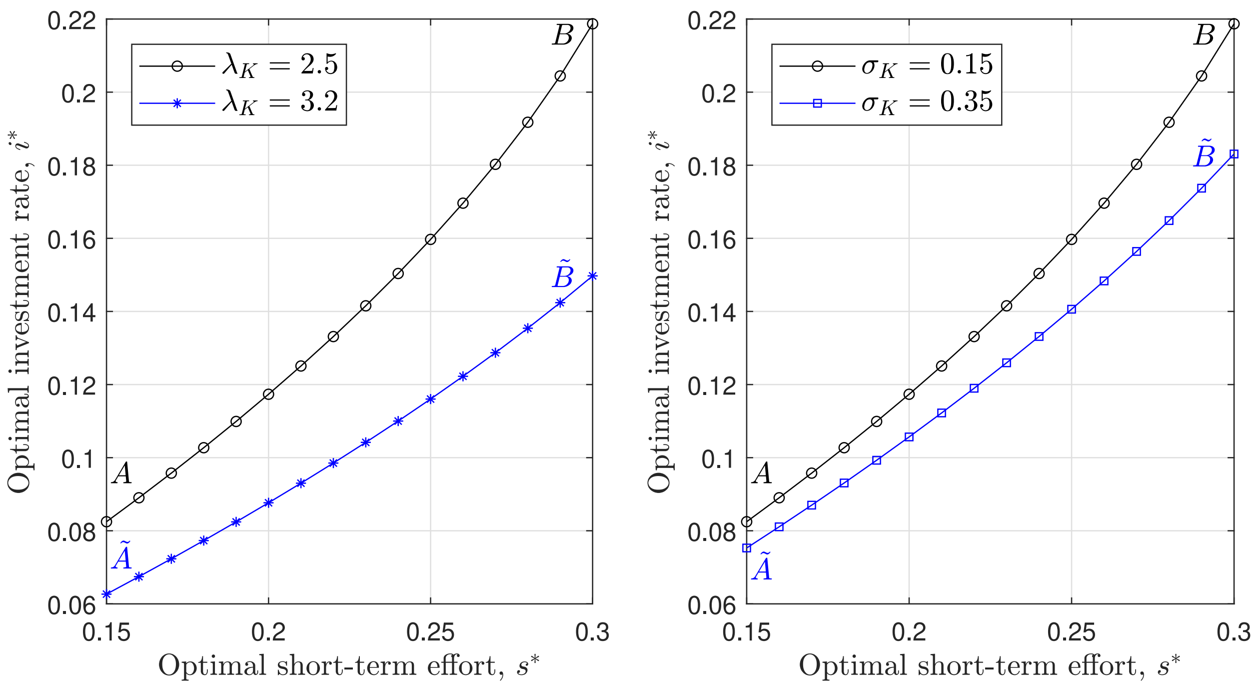

Figure 1: Model comparative statics. The figure plots the combinations of optimal investment rate, i^*, and optimal short-term effort s^*, as short-term effort adjustment costs, λ_s, vary between 3.33 (points A and $\tilde{A}$) and 6.66 (points B and $\tilde{B}$). For the black lines in either panel, 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 blue lines, the parameters are the same expect $\lambda_K = 3.2$ and $\sigma_K = 0.35$. On the left panel, the blue line is for a higher value of capital adjustment costs ($\lambda_K = 3.2$). On the right panel, the blue line is for a higher capital shocks volatility ($\sigma_K = 0.35$) and low ($\sigma_K = 0.15$).

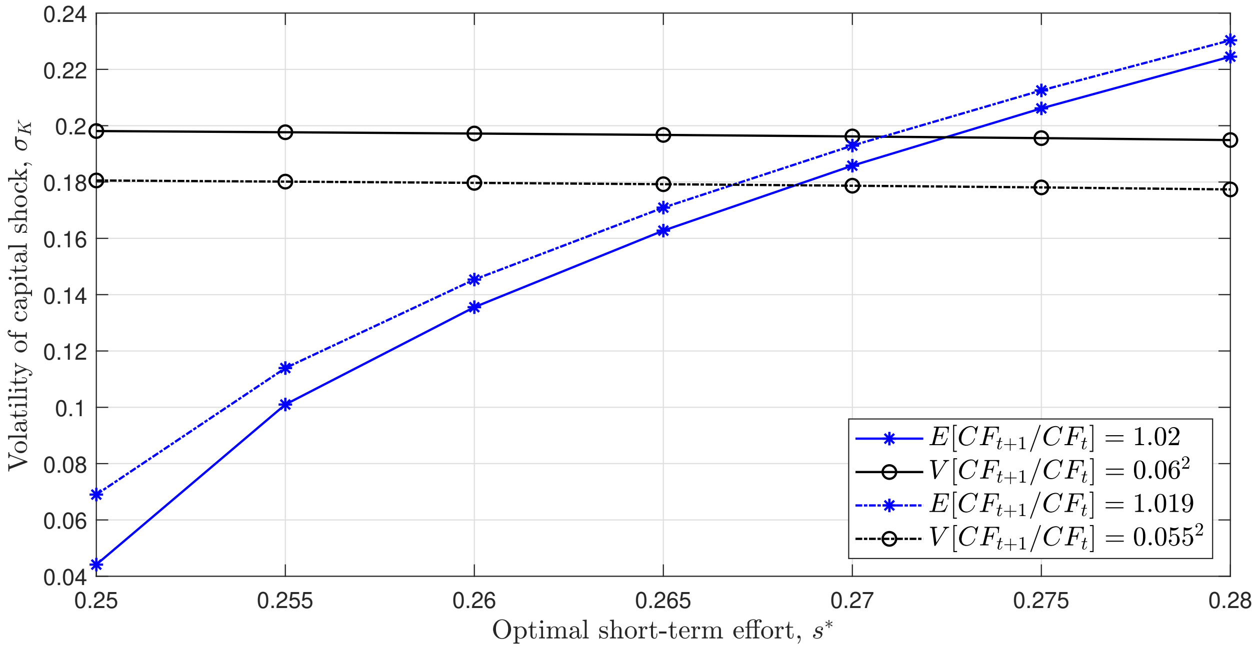

Figure 2: Sensitivity of model-implied moments to s^* and σ_K. The figure plots two maps of iso-curves. Each curve in blue represents all the combinations of values for the short-term effort policy, s^*, and the volatility of shocks to the capital stock, σ_K, that imply the same expected earnings growth rate, $E[CF_{t+1}/CF_t]$, all else constant. For the blue solid line, the earnings growth rate is 2%; for the blue dash-dotted line, it is 1.9%. Each curve in black represents the combinations of s^* and σ_K that imply the same earnings growth variance, $V[CF_{t+1}/CF_t]$, *ceteris paribus*: 0.36% for the solid line and 0.3% for the dash-dotted line.

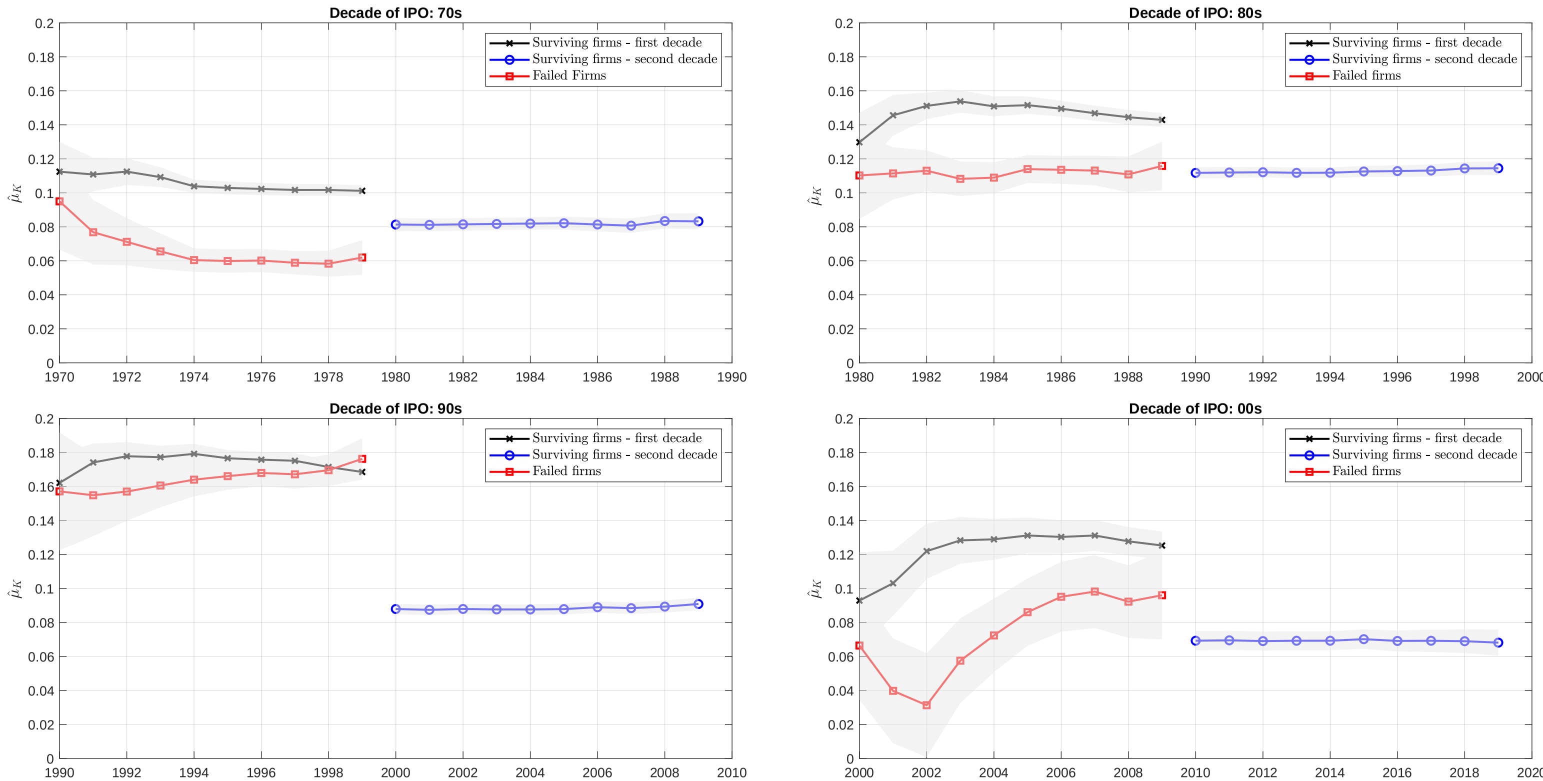

Figure 3: The growth rate of the capital stock over time. This figure plots the time series of the average estimated growth rate of the capital stock, $\hat{\mu}_K$, during the decade in which a firm went public and during the subsequent decade. For the first decade, the model is estimated separately 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.

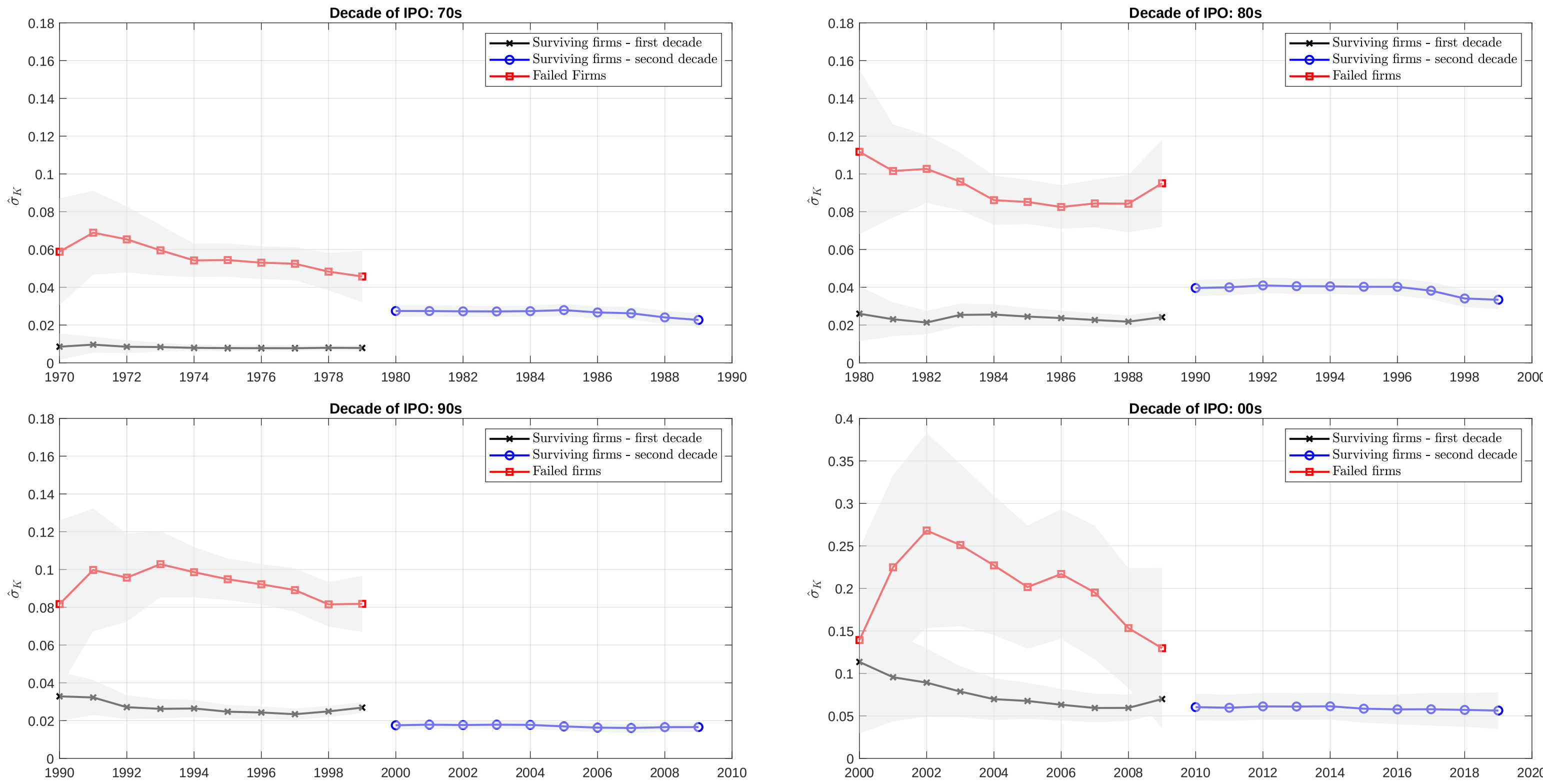

Figure 4: The volatility of the capital stock over time. This figure plots the time series of the average estimated volatility of the capital stock growth rate, $\hat{\sigma}_K$, during the decade in which a firm went public and during the subsequent decade. For the first decade, the model is estimated 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.

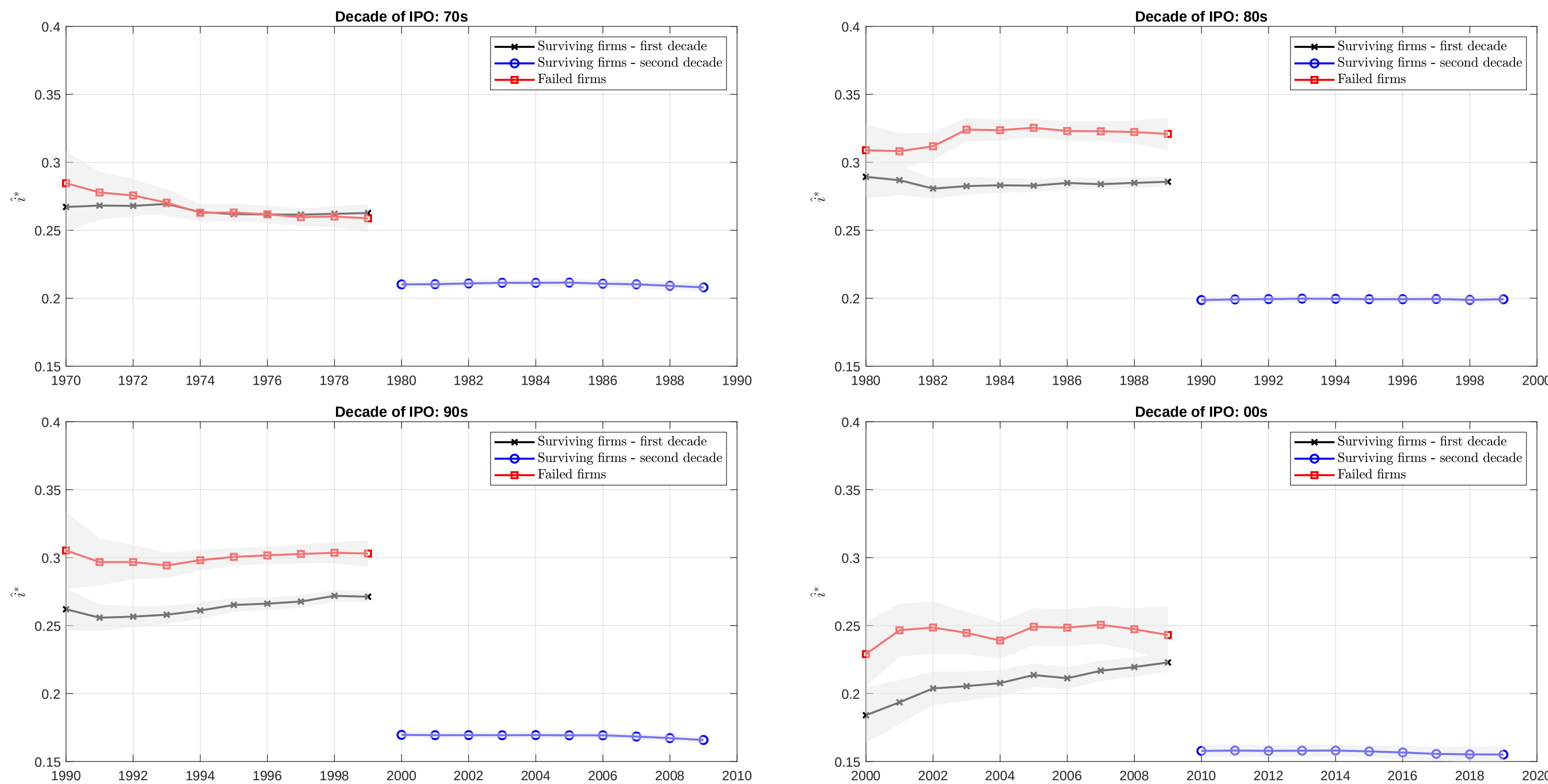

Figure 5: The investment rate over time. This figure plots the time series of the average estimated investment rate, $\hat{i}^*$, during the decade in which a firm went public and during the subsequent decade. For the first decade, the model is estimated separately for firms that failed and were de-listed (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.

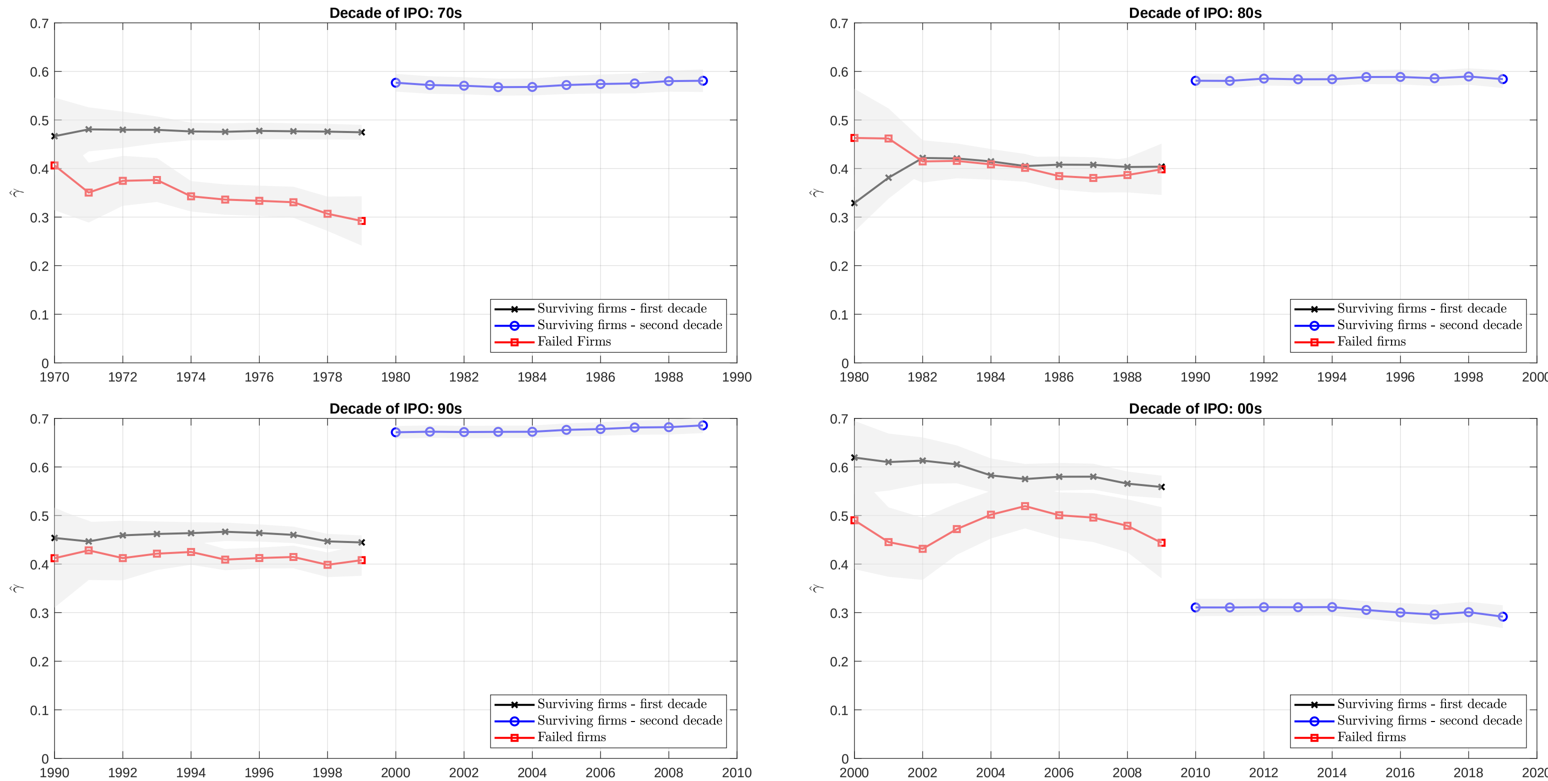

Figure 6: The capital elasticity of earnings over time. The figure plots the time series of the average estimated elasticity of earnings with respect to capital, γ, during the decade in which a firm went public and during the subsequent decade. For the first decade, the model is estimated separately 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.

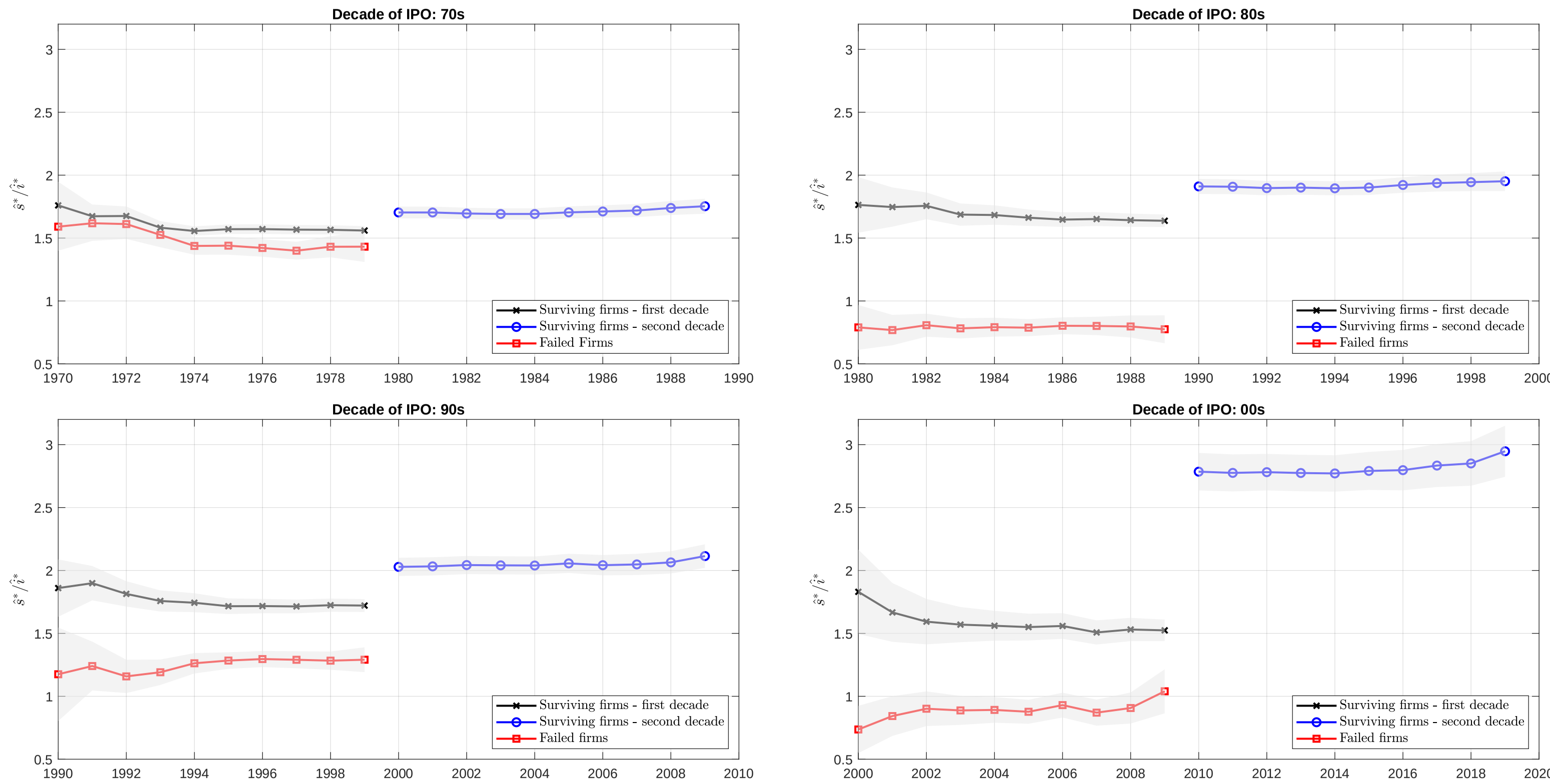

Figure 7: The short-term effort-to-investment ratio over time. The figure plots the time series of the average estimated short-term effort-to-investment ratio, $\hat{s}^*/\hat{i}^*$, during the decade in which a firm went public and during the subsequent decade. For the first decade, the model is estimated 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.

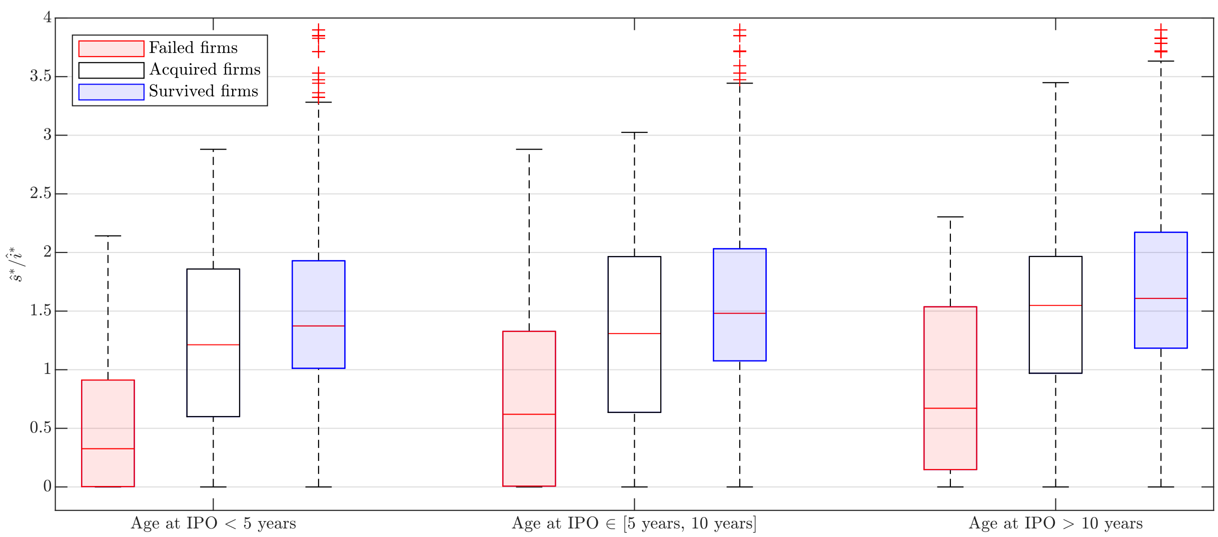

Figure 8: Firm age and short-term effort-to-investment ratio during the IPO decade. The figure shows the distribution of the estimated ratio of short-term effort to investment, $\hat{s}^*/\hat{i}^*$, during the decade in which the firm went public, conditional on the age of the firm at the IPO and whether 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.

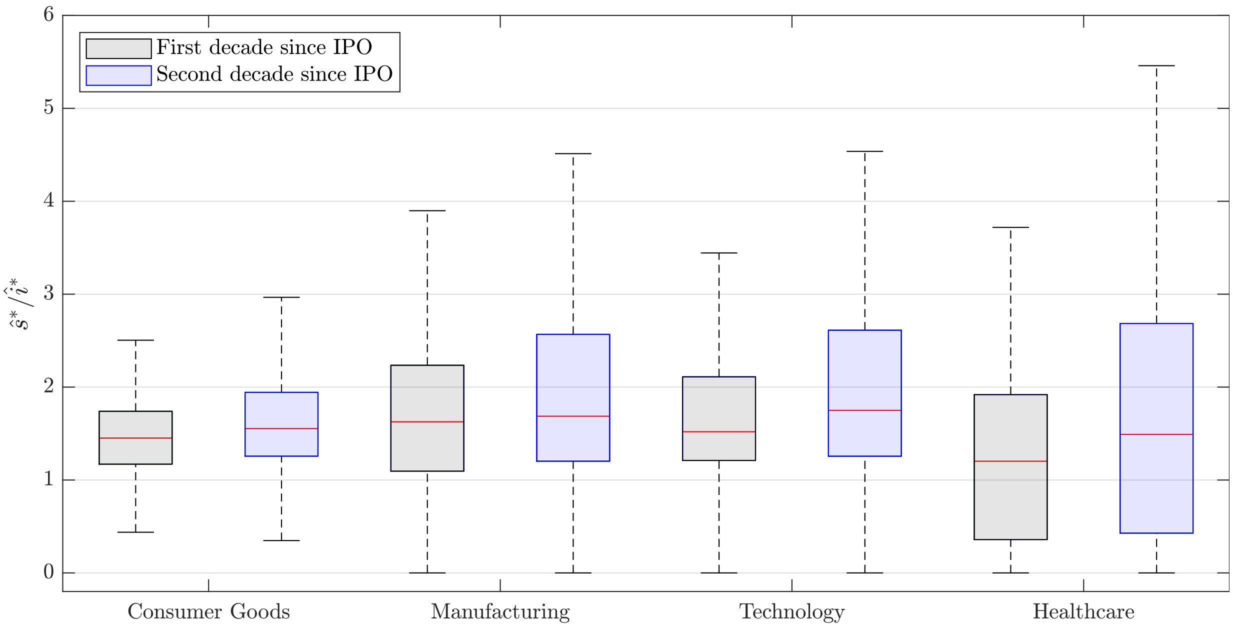

Figure 9: The short-term effort-to-investment ratio across industries. The figure shows the distribution of the estimated ratio of short-term effort to investment, $\hat{s}^*/\hat{\imath}^*$, during the decade in which the firm went public and during the subsequent decade for the four major groups in 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.

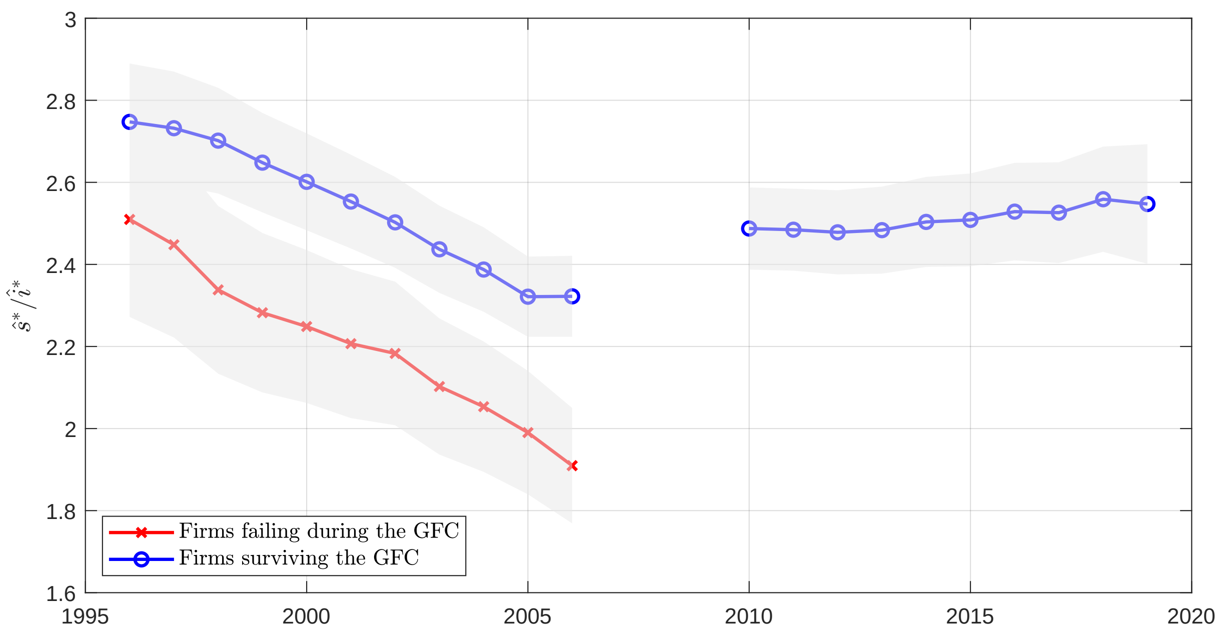

Figure 10: The short-term effort-to-investment ratio around the Great Financial Crisis. This figure plots the time series of the average estimated short-term effort-to-investment ratio, $\hat{s}^*/\hat{i}^*$, for the ten-year periods before and after the Great Financial Crisis of 2007 to 2009. For the 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.

Table 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 (2017): Ebitda (oibdp) + R&D expense + 0.3 × SG&A expenses
Capital	Stock of tangible plus intangible capital, computed as in Peters and Taylor (2017)
Investment	Investment in tangible & intangible assets, as defined by Peters and Taylor (2017): 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. (2020)
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 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 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: Summary of the model's parameters and policies estimates
This table summarises the maximum likelihood estimates of the model equations (12)–(18). 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							
$\hat{i}^*$	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
$\hat{s}^*$	0.29	0.20	0.00	0.17	0.27	0.38	0.64
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
$\hat{s}^*$	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 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 (12)–(18) 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
$\hat{s}^*$	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
$\hat{s}^*/\hat{i}^*$	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
$\hat{s}^*$	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
$\hat{s}^*/\hat{i}^*$	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 4 -*continued*

Panel B: Changes in estimates between decades[†]

		Consumer Goods	Manufacturing	Technology	Healthcare
$\Delta\hat{s}^*/\hat{i}^*$	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		248	234	316	98

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

Table 5: Interdecadal changes in short-term effort and investment policies
This table presents estimates from cross-sectional regressions of the change in the estimated short-term effort-to-investment ratio, $\Delta s^*/i^*$, from the decade of the firm's IPO to the next, on binary variables indicating the decade in which the firms went public (1{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*
	(0.111)	(0.130)	(0.124)	(0.204)
1{IPO in 80s}	−0.219	0.091	0.635***	0.658**
	(0.163)	(0.182)	(0.155)	(0.317)
1{IPO in 90s}	1.011**	0.600**	1.021***	−0.398
	(0.414)	(0.239)	(0.213)	(0.289)
1{IPO in 00s}	0.156	0.084	0.692**	2.599***
	(0.194)	(0.366)	(0.296)	(0.269)
1{IPO in 70s} $\times\Delta\hat{\sigma}_K$	−4.599**	−1.330	0.902	8.966**
	(1.902)	(0.910)	(0.869)	(3.413)
1{IPO in 80s}$\times\Delta\hat{\sigma}_K$	7.808***	1.455	−0.591	−7.961**
	(2.302)	(1.170)	(1.178)	(3.854)
1{IPO in 90s}$\times\Delta\hat{\sigma}_K$	−4.061	1.569	2.109	−8.621**
	(4.798)	(1.258)	(1.691)	(3.529)
1{IPO in 00s}$\times\Delta\hat{\sigma}_K$	5.795***	−0.580	−12.316**	−19.099***
	(1.966)	(1.274)	(6.174)	(5.232)
1{IPO in 70s}$\times\Delta\hat{\gamma}$	−1.756***	−0.121	−1.430***	−1.727***
	(0.319)	(0.432)	(0.346)	(0.588)
1{IPO in 80s}$\times\Delta\hat{\gamma}$	0.111	−0.840*	−1.150***	−0.964
	(0.314)	(0.447)	(0.310)	(0.657)
1{IPO in 90s}$\times\Delta\hat{\gamma}$	−2.474***	−1.897***	−1.456***	0.114
	(0.851)	(0.460)	(0.385)	(0.544)
1{IPO in 00s}$\times\Delta\hat{\gamma}$	0.628	−5.211***	−1.478**	8.553***
	(0.513)	(1.662)	(0.703)	(0.990)
Number of Observations	248	234	316	98
R^2	0.442	0.629	0.430	0.422

Table 6: Cross-sectional regressions of short-term effort and investment policies This table presents estimates from cross-sectional regressions of the estimated short-term effort, s^*, investment, i^*, and short-term effort-to-investment ratio, s^*/i^* on binary variables indicating the decade in which the firms went public, i.e., 1{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		
	$\hat{s}^*$	$\hat{i}^*$	$\hat{s}^*/\hat{i}^*$	$\hat{s}^*$	$\hat{i}^*$	$\hat{s}^*/\hat{i}^*$	$\hat{s}^*$	$\hat{i}^*$	$\hat{s}^*/\hat{i}^*$
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)	(0.032)	(0.010)	(0.150)	(0.054)	(0.008)	(0.301)
$\hat{\sigma}_K$	0.054	0.039	−0.018	−0.102*	−0.056***	0.128	−0.069	0.013	−0.317
	(0.098)	(0.032)	(0.293)	(0.058)	(0.016)	(0.414)	(0.045)	(0.009)	(0.256)
$\hat{\gamma}$	0.075	−0.006	0.124	−0.205***	−0.001	−0.869***	−0.508***	−0.005	−3.026***
	(0.058)	(0.028)	(0.220)	(0.028)	(0.010)	(0.113)	(0.057)	(0.006)	(0.326)
1{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)	(0.018)	(0.007)	(0.076)	(0.019)	(0.005)	(0.089)
1{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)	(0.016)	(0.006)	(0.072)	(0.022)	(0.005)	(0.126)
1{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)	(0.022)	(0.009)	(0.094)	(0.030)	(0.006)	(0.162)
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)	(0.018)	(0.007)	(0.097)	(0.027)	(0.004)	(0.176)
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)	(0.020)	(0.007)	(0.114)	(0.026)	(0.004)	(0.155)
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)	(0.021)	(0.008)	(0.104)	(0.029)	(0.005)	(0.145)
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)	(0.036)	(0.009)	(0.146)	(0.036)	(0.005)	(0.197)
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)	(0.003)	(0.001)	(0.015)	(0.004)	(0.001)	(0.022)
Observations	839	839	839	4,736	4,736	4,736	6,126	6,126	6,126
R^2	0.183	0.359	0.103	0.235	0.393	0.143	0.257	0.367	0.244

Table 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. (2020) price-marginal cost markup (Panel A) or the logarithm of total annual sales (Panel B) on the estimates of short-term effort, s^* 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
$\hat{s}^*$	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
$\hat{s}^*$	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 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. (2020) price-marginal cost markup, the logarithm of total annual sales, and sales growth from the IPO decade to the next on the estimates of short-term effort, s^* 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	
$\hat{s}^*$	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 9: Predictive regressions of product market outcomes
This table presents estimates from regressions of the De Loecker et al. (2020) 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 short-term effort, s^* 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
$\hat{s}^*$	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
$\hat{s}^*$	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 9 -*continued*

Panel C: Sale Growth

	Period 1		Period 2		Period 3	
	OLS	Heckman	OLS	Heckman	OLS	Heckman
$\hat{s}^*$	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 10: Optimal s^*, 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 short-term effort, s^*, 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 3.5) 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}
$\hat{s}^*$	-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